THE MACROECONOMIC IMPACT OF FINANCIAL AND UNCERTAINTY SHOCKS

Dario Caldara
Cristina Fuentes-Albero
Simon Gilchrist
Egon Zakrajšek

The Macroeconomic Impact of Financial and Uncertainty Shocks
Dario Caldara, Cristina Fuentes-Albero, Simon Gilchrist, and Egon Zakrajšek
NBER Working Paper No. 22058
March 2016
JEL No. E32,E37,E44

ABSTRACT

The extraordinary events surrounding the Great Recession have cast a considerable doubt on the traditional sources of macroeconomic instability. In their place, economists have singled out financial and uncertainty shocks as potentially important drivers of economic fluctuations. Empirically distinguishing between these two types of shocks, however, is difficult because increases in economic uncertainty are strongly associated with a widening of credit spreads, an indication of a tightening in financial conditions. This paper uses the penalty function approach within the SVAR framework to examine the interaction between financial conditions and economic uncertainty and to trace out the impact of these two types of shocks on the economy. The results indicate that (1) financial shocks have a significant adverse effect on economic outcomes and that such shocks were an important source of cyclical fluctuations since the mid-1980s; (2) uncertainty shocks, especially those implied by uncertainty proxies that do not rely on financial asset prices, are also an important source of macroeconomic disturbances; and (3) uncertainty shocks have an especially negative economic impact in situations where they elicit a concomitant tightening of financial conditions. Evidence suggests that the Great Recession was likely an acute manifestation of the toxic interaction between uncertainty and financial shocks.

Dario Caldara
Federal Reserve Board
20th Street and Constitution Avenue, NW,
Washington, DC 20551
dario.caldara@frb.gov

Cristina Fuentes-Albero
Federal Reserve Board
20th Street and Constitution Avenue, NW,
Washington, DC 20551
Cristina.Fuentes-Albero@frb.gov

Simon Gilchrist
Department of Economics
Boston University
270 Bay State Road
Boston, MA 02215
and NBER
sgilchri@bu.edu

Egon Zakrajšek
Division of Monetary Affairs
Federal Reserve Board
20th Street & Constitution Avenue, NW
Washington, D.C. 20551
egon.zakrajsek@frb.gov

1 Introduction

The acute turmoil that swept through global financial markets during the 2008–09 financial crisis and the depth and duration of the associated economic downturn, both in the United States and abroad, have cast a considerable doubt on the traditional sources of business cycle fluctuations. In response, recent theoretical and empirical research aimed at understanding these extraordinary events has pointed to financial and uncertainty shocks—or their combination—as alternative drivers of economic fluctuations (Bloom, 2009; Bloom et al., 2012; Arellano et al., 2012; Christiano et al., 2014; Gilchrist et al., 2014).

Empirically distinguishing between these two types of shocks, however, is difficult because increases in financial market volatility—a widely used proxy for macroeconomic uncertainty—are frequently associated with significant increases in credit spreads. A stark illustration of this empirical challenge is depicted in Figure 1, which shows the relationship between the daily change in the option-implied volatility on the S&P 500 stock futures index (the VIX) and the daily change in the speculative-grade CDX index during the recent financial crisis.[1] Clearly evident is the fact that episodes of acute financial distress are associated with spikes in asset price volatility. Indeed, in their comprehensive empirical anatomy of the Great Recession, Stock and Watson (2012) explicitly single out the high (positive) correlation between credit spreads and proxies for economic uncertainty and conclude that "[T]hese two sets of instruments do not seem to be identifying distinct shocks."

Within a structural vector autoregressive (SVAR) framework—the workhorse of empirical macroeconomics—this high degree of comovement between indicators of financial distress such as credit spreads and uncertainty proxies significantly complicates the identification of financial and uncertainty shocks, as both types of variables are "fast moving." As a result, it is difficult to impose plausible zero contemporaneous restrictions to identify these two types of disturbances. It it also difficult to impose sign restrictions on the impulse response functions in order to achieve an economically plausible identification because financial and uncertainty shocks have theoretically the same qualitative effects on both prices and quantities in most instances.

In this paper, we use the penalty function approach developed initially by Faust (1998) and Uhlig (2005) to examine the interaction of economic uncertainty and financial conditions and to trace out the impact of the associated shocks on the macroeconomy. Within our SVAR framework, these two structural innovations are identified using a criterion that each shock should maximize the *impulse response* of its respective target variable over a pre-specified horizon. In economic terms, our identified uncertainty and financial shocks generate a prolonged period of heightened

---

[1]The VIX index is a commonly used proxy for macroeconomic uncertainty (Bloom, 2009, 2014). The speculative-grade CDX index is a tradable credit derivative index used widely by investors for hedging of and investing in corporate credit risk. Buying and selling of the credit derivative index is comparable to buying and selling portfolios of corporate bonds: By buying the index, the investor takes on the credit exposure—is exposed to defaults—a position similar to that of buying a portfolio of bonds; by selling the index, the credit exposure is passed on to another party. The speculative-grade CDX index references 100 (5-year) credit default swap (CDS) contracts on firms that have a "junk" rating from either Moody's or Standard & Poor's. The component firms must have highly liquid single-name CDS trading in their name, and the composition of both indexes, which is determined by a dealer poll, is representative of the U.S. corporate sector.

FIGURE 1: Financial Market Volatility and Credit Risk During the Great Recession
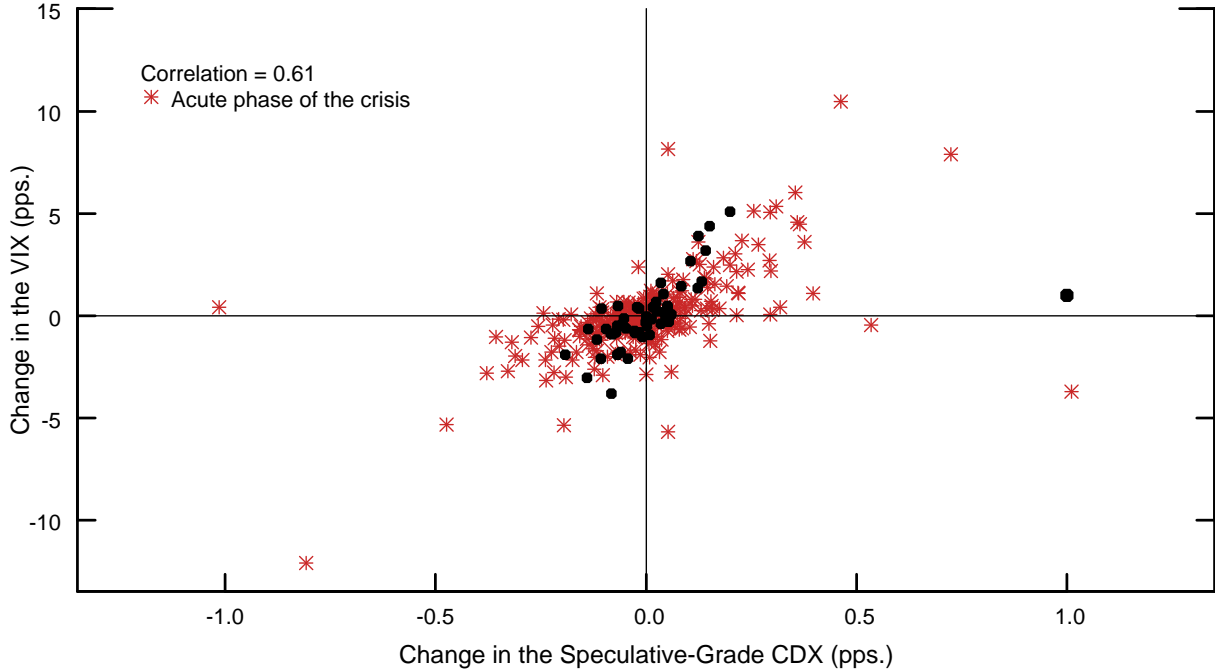
NOTE: Sample period: daily data from 12/01/2007 to 06/30/2009. The scatter plot depicts the relationship between the daily change in the option-implied volatility on the S&P 500 stock futures index (VIX) and the daily change in the 5-year (on-the-run) speculative-grade CDX index. The period 09/01/2008 to 08/05/2009 marks the acute phase of the crisis, which reached a critical stage in early September 2008, when an evaporation of liquidity in the global credit markets threatened the solvency of several major financial institutions. The end date of the acute phase follows the release of the results from the Supervisory Capital Assessment Program (the so-called bank stress test) at 5 p.m. EST on May 7, 2009.

economic uncertainty and a persistent tightening of financial conditions, respectively. Moreover, our identifying assumptions allow for financial conditions to react immediately to an uncertainty shock, while financial shocks can also have a contemporaneous effect on the level of economic uncertainty.[2] Compared with identification schemes based on sign restrictions, this framework allows us to distinguish empirically between shocks that have otherwise very similar qualitative effects on the economy.

Our approach, however, still requires a sequential identification of these two shocks. As a result, we implement the penalty function criterion in two steps. Under the baseline identification scheme,

---

[2]To the best of our knowledge, there are only two studies that analyze the effects of both financial and uncertainty shocks in the VAR context. Focusing on the German economy, Popescu and Smets (2010) identify financial and uncertainty shocks using a recursive ordering, in which the uncertainty proxy is placed after the macro block but before the financial market risk index—that is, they allow uncertainty shocks to elicit an immediate change in financial conditions but not vice versa. Gilchrist et al. (2014) use U.S. data to explore the macroeconomic implications of uncertainty and financial shocks using alternative orderings for the uncertainty and financial stress proxies. The key finding that emerges from their analysis is that the economic significance of uncertainty shocks hinges crucially on whether they have been orthogonalized with respect to the contemporaneous information in credit spreads. This result highlights the need for an approach that allows for a contemporaneous feedback between financial conditions and economic uncertainty.

we first search for an innovation that maximizes the response of the uncertainty proxy over a given horizon—this optimization step identifies what we call an "uncertainty shock." In the second step, we search for an innovation that maximizes the response of an indicator of financial conditions over the same horizon and that is orthogonal to the uncertainty shock identified in the first step—we call this shock a "financial shock." To examine the robustness of the assumptions underlying our baseline identification scheme, we also consider an alternative strategy that reverses the ordering of the two penalty function steps used to identify these two disturbances.

We implement the penalty function approach to multiple shock identification in the context of a standard monetary VAR, augmented with a measure of the tightness of financial conditions and an uncertainty proxy. To measure financial market strains, we use the excess bond premium, an indicator of the effective "risk-bearing capacity" of the financial intermediary sector, developed recently by Gilchrist and Zakrajšek (2012). Reflecting the amorphous concept of economic uncertainty, we examine the macroeconomic implications of uncertainty shocks implied by six widely used uncertainty proxies. Three of these proxies are based on stock market volatility, one is the well-known index of economic policy uncertainty developed by Baker et al. (2015), while the remaining two proxies are based on real economic activity; the latter two uncertainty measures correspond to the survey-based measure of forecast dispersion constructed by Bachmann et al. (2013) and a measure of dispersion in forecast errors constructed from a statistical model developed recently by Jurado et al. (2015).

We begin our analysis with a simple forecasting exercise, in which we compare the ability of these six uncertainty measures to forecast economic activity relative to the excess bond premium.[3] While the excess bond premium provides economically important and statistically significant gains in predicting the course of future economic activity, we find that only the two measures of uncertainty based on economic activity provide marginal improvements in forecasting power.

We then turn to an analysis of the role that uncertainty and financial shocks play in explaining macroeconomic outcomes in the VAR framework described above. Under the identification scheme that orders uncertainty first, we find that uncertainty shocks have an economically and statistically significant impact on both the stock market and real economic activity. This result holds true for all six uncertainty proxies, though the estimated declines in economic activity are appreciably larger in response to uncertainty shocks implied by the two uncertainty measures based on real economic data. Importantly, under this identification scheme, an increase in uncertainty also leads to a deterioration in financial conditions as measured by an increase in the excess bond premium, a result that highlights the close relationship between swings in economic uncertainty and changes in financial market conditions.

Under the alternative identification scheme—in which uncertainty is ordered after the excess bond premium—the effect of an uncertainty shock varies significantly across the different uncertainty proxies. For the two proxies based on real economic data, we find that uncertainty shocks

---

[3]Gilchrist and Zakrajšek (2012) provide extensive evidence on the predictive content of credit spreads for economic activity in general and the excess bond premium in particular.

again induce significant declines in real economic activity, although unsurprisingly, the effects are substantially attenuated relative to the identification scheme in which uncertainty is ordered first. Strikingly, under this second identification scheme, uncertainty shocks measured with either stock market data or economic policy news have no economically discernible effect on macroeconomic outcomes.[4]

Given the robustness of the results obtained using uncertainty proxies implied by real economic data, the remainder of our analysis explores the macroeconomic implications of uncertainty and financial shocks using the Jurado et al. (2015) measure of uncertainty, along with the excess bond premium to measure strains in financial markets. According to our results, both financial and uncertainty shocks have robust negative effects on economic activity that are quite similar in magnitude—they both imply a contraction in real industrial output between 0.6 percent and 1 percent, depending on the identification scheme. Forecast error variance decompositions imply that these two shocks account for 20 percent to 40 percent of the variability in industrial production at business cycle frequencies, again depending on the identification scheme. Historical variance decompositions further underscore the important role played by these two shocks in explaining both economic outcomes and fluctuations in the stock market. Notably and consistent with the findings of Stock and Watson (2012), the combination of financial and uncertainty shocks fully accounts for the contraction in economic activity and the collapse of the stock market during the Great Recession.

The final step of our analysis considers an external validation exercise, in which we explore the extent to which shocks to economic uncertainty and financial conditions are, in fact, independent sources of macroeconomic instability, or whether they reflect endogenous responses to more traditional sources of business cycle fluctuations. Specifically, we study the extent to which both uncertainty and financial shocks are correlated with alternative measures of business cycle disturbances, such as unanticipated shifts in the stance of monetary policy and shocks to technology, oil prices, and government spending. Consistent with Stock and Watson (2012), we find that our shocks to both uncertainty and financial market conditions are completely uncorrelated with any such external instrument.

The literature on the effects of uncertainty on macroeconomic outcomes has emphasized real options effects that lead to declines in business investment (Bloom, 2009; Bloom et al., 2012); financial mechanisms whereby the cost of external finance increases in response to a rise in uncertainty (Arellano et al., 2012; Christiano et al., 2014; Gilchrist et al., 2014); feedback mechanisms through which reduced economic activity leads to heightened macroeconomic uncertainty (Van Nieuwerburgh and Veldkamp, 2006; Fajgelbaum et al., 2014); and difficulties in forecasting economic variables during recessions (Orlik and Veldkamp, 2014). Our results imply that increases in uncertainty that are associated with a tightening of financial conditions have particularly pow-

---

[4]Recent work by Ludvigson et al. (2016) provides an alternative measure of financial uncertainty and a novel identification scheme, which suggests that it is financial, rather than real, uncertainty that drives the business cycle. These disparate results may be due to the difference between financial uncertainty and stock market volatility and possibly account for the extent to which financial uncertainty comoves with the excess bond premium.

erful adverse effects on real economic activity and the stock market, a finding that is consistent with models in which uncertainty shocks are amplified via a reduction in the supply of credit. It is also consistent with the recent theoretical work of Brunnermeier and Sannikov (2014), in which a deterioration in borrowers' balance sheet conditions can induce greater financial market volatility.

It is worth emphasizing, however, that all of the channels describe above are, to a large extent, complementary mechanism, which may simultaneously lead to heightened uncertainty, a tightening of financial conditions, and a collapse in economic activity. Nonetheless, the finding that both uncertainty and financial shocks are uncorrelated with other measurable external shocks suggests that there are limitations to the argument that increased uncertainty and the concomitant deterioration in financial conditions are purely endogenous responses to fluctuations in economic activity over the normal course of the business cycle. Rather, our results underscore that the interplay between heightened uncertainty and increased financial fragility have independent and deleterious consequences for both asset valuations and macroeconomic outcomes.

2 Uncertainty, Financial Conditions, and Economic Activity

2.1 Measuring Uncertainty and Financial Conditions

Economic uncertainty is difficult to quantify. As a result, the empirical literature is awash with different uncertainty proxies and new measures crop up all the time (Bloom, 2014). Because there is little consensus among economists on what is the best measure of economic uncertainty, rather than taking a stand on any particular indicator, we consider six different proxies, which span the range of methodological approaches used to infer fluctuations in economic uncertainty at monthly frequency.

Our first three uncertainty proxies are based on stock market data. Because financial asset prices, in principle, encompass all aspects of the firm's environment that the investors view as important, much research in this area relies on stock prices to infer fluctuations in both the microeconomic and macroeconomic uncertainty. The first uncertainty proxy used in our analysis is the realized stock market volatility (**RVOL**), a model-free measure that is especially simple to construct. We also consider the option-implied volatility on the S&P 100 stock futures index constructed by the Chicago Board of Option Exchange (**VXO**).[5]

While intuitive and readily available, the RVOL and VXO uncertainty proxies are a combination of two factors: the actual realized or expected stock market volatility—that is, stock market uncertainty—and a factor containing information about risk and risk aversion. As emphasized by Bekaert et al. (2013), the risk component is highly countercyclical. In our context, therefore, using these two uncertainty proxies to jointly identify uncertainty and financial shocks is likely to confound their respective effect on the macroeconomy. Gilchrist et al. (2014) try to circumvent

---

[5]We use the VXO, as opposed to the VIX option-implied volatility, because the VXO is available starting in January 1986, compared with January 1990, the starting date for the VIX. The correlation between these two indicators, however, is almost 0.99 at a monthly frequency.

FIGURE 2: Financial Market Conditions
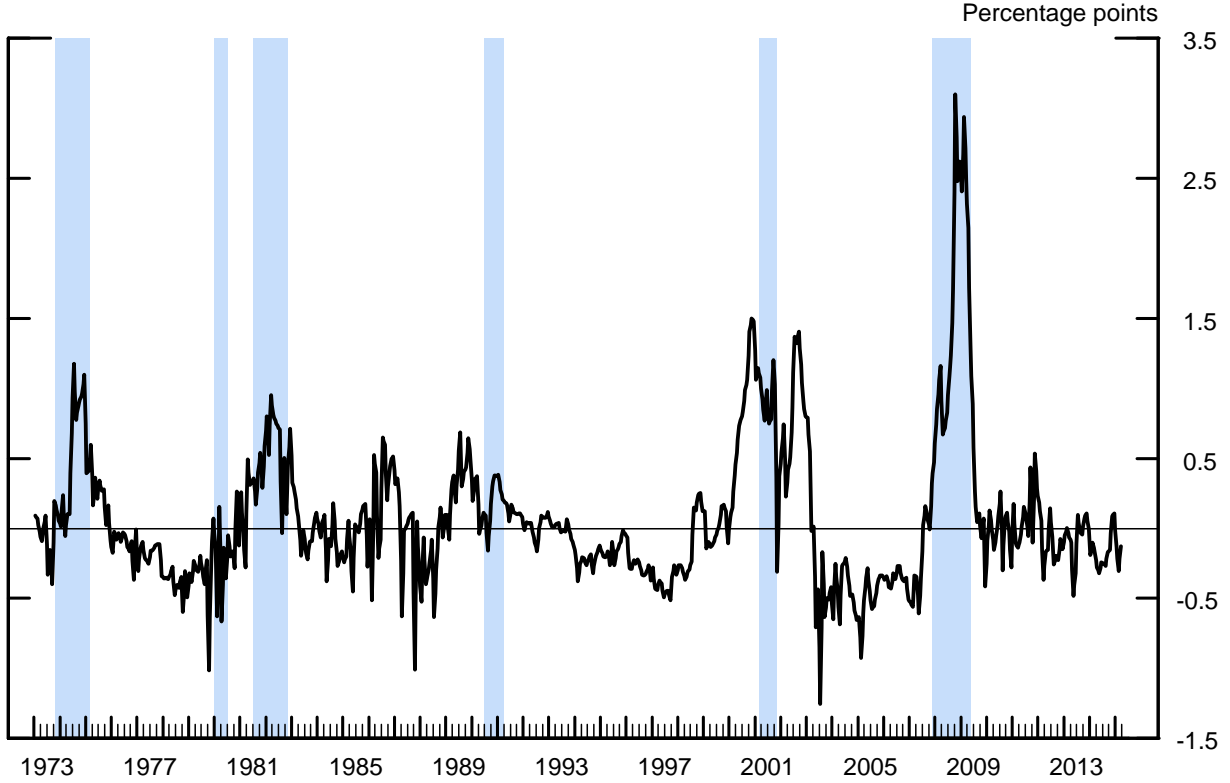
NOTE: Sample period: monthly data from 1973:M1 to 2015:M3. The solid line shows the excess bond premium, an indicator of the tightness of broad financial market conditions; see Gilchrist and Zakrajšek (2012) and the text for details. The shaded vertical bars denote the NBER-dated recessions.

this problem by purging (excess) stock returns of their systematic variation using a set of standard empirical risk factors. Their uncertainty measure (**IVOL**), which captures common shocks in the idiosyncratic volatility of equity returns, is our third proxy and one that is less likely to reflect the countercyclical nature of contractual and informational frictions associated with financial shocks.

Nevertheless, we also look beyond the stock market to infer fluctuations in macroeconomic uncertainty. Our first such measure is the economic uncertainty index proposed by Jurado et al. (2015), which is based on the implied forecast errors for real economic activity derived from a factor model that utilizes hundreds of economic and financial series (**JLN**).[6] Next is the widely cited index of economic policy uncertainty developed by Baker et al. (2015) (**BBD**), which captures the frequency of words in major U.S. newspapers associated with uncertainty regarding economic policy. And our last proxy for macroeconomic uncertainty, put forth by Bachmann et al. (2013), is a measure of forecast dispersion constructed using the Philadelphia Fed's Business Outlook Survey (**BES**). Details concerning the construction of the various uncertainty measures are contained in

---

[6]Throughout the paper, we use the JLN measure of uncertainty at the 3-month forecast horizon; our results, however, were robust to both shorter (1-month) and longer (12-month) horizons.

TABLE 1: Cross-Correlations Between the EBP and Different Uncertainty Proxies

Lag/Lead (h)	RVOL	IVOL	VXO	JLN	BBD	BES
-3	0.47***	0.25***	0.51***	0.46***	0.37***	0.02
-2	0.52***	0.28***	0.54***	0.49***	0.39***	0.08*
-1	0.58***	0.33***	0.58***	0.51***	0.40***	0.09*
0	0.59***	0.34***	0.59***	0.52***	0.42***	0.12**
1	0.60***	0.39***	0.59***	0.52***	0.39***	0.12***
2	0.54***	0.33***	0.53***	0.51***	0.32***	0.14***
3	0.52***	0.31***	0.48***	0.50***	0.28***	0.14***

NOTE: The entries in the table denote the cross-correlations between the EBP in month t and the specified uncertainty proxy in month $t + h$. RVOL = realized equity volatility (1973:M1–2015:M3, $T = 507$); IVOL = idiosyncratic equity volatility based on Gilchrist et al. (2014) (1973:M1–2015:M3, $T = 507$); VXO = option-implied volatility on the S&P 100 stock futures index (1986:M1–2015:M3, $T = 351$); JLN = uncertainty measure based on Jurado et al. (2015) (1973:M1–2015:M3, $T = 507$); BBD = uncertainty measure based on Baker et al. (2015) (1985:M1–2015:M3, $T = 363$); and BES = uncertainty measure based on Bachmann et al. (2013) (1973:M1–2011:M12, $T = 468$). * $p < .10$, ** $p < .05$, and *** $p < .01$.

Appendix A.

To measure the tightness of financial market conditions, we rely on corporate bond credit spreads.[7] Specifically, we use the excess bond premium (EBP) of Gilchrist and Zakrajšek (2012) (GZ hereafter), an estimate of the extra compensation demanded by bond investors for bearing exposure to U.S. nonfinancial corporate credit risk, above and beyond the compensation for expected losses.[8] As emphasized by GZ, the corporate cash market is served by major financial institutions and fluctuations in the EBP thus capture shifts in the risk attitudes of these institutions and their willingness to bear credit risk and to intermediate credit more generally.[9]

The solid line in Figure 2 shows this indicator of broad financial conditions over the 1973:M1–2015:M12 period, while Table 1 displays the pairwise cross-correlations between the EBP and the different uncertainty proxies at various leads and lags. Note that the cross-correlations between the tightness of financial conditions and economic uncertainty are all positive and tend to be the highest at $h = 0$, that is, contemporaneously. Moreover, there is a substantial degree of comovement between the EBP and various uncertainty proxies at the near-term horizons, underscoring the close relationship between changes in financial conditions and swings in economic uncertainty over the course of a business cycle.

---

[7]The fact that corporate bond credit spreads are highly informative about the tightness of financial conditions in the economy and thus the implied degree of departure from the Modigliani–Miller paradigm of frictionless financial markets is supported by large empirical literature, which shows that credit spreads form the most informative and reliable class of financial indicators for future economic activity and that unanticipated increases in credit spreads have large and persistent adverse effects on the macroeconomy (Gilchrist et al., 2009; Gilchrist and Zakrajšek, 2012; Boivin et al., 2013; Faust et al., 2013).

[8]The EBP is effectively a measure of credit spreads net of an estimate of default risk and thus has a natural interpretation of an expected credit return, In netting out default risk, we make a small modification to the original GZ methodology. Specifically, we allow the conditional variance of the (log) credit spread "pricing errors" to vary over time. However, all of the results reported in the paper are virtually the same if the conditional variance of the error term in the GZ credit spread pricing regression is assumed to be constant over time.

[9]See Adrian and Shin (2010), and López-Salido et al. (2016) for related empirical evidence.

This holds true even for uncertainty proxies such as JLN and BBD, which are not explicitly based on financial market data. One clear exception to this pattern is the BES uncertainty proxy—a measure based on the survey respondents' disagreement regarding future economic outcomes—the past values of which appear to be largely uncorrelated with future fluctuations in the EBP; on the other hand, a tightening of financial conditions is mildly indicative of a future increase in this uncertainty indicator. In sum, these results highlight the need for analysis that explicitly incorporates the interaction between economic uncertainty and financial conditions.

2.2 Uncertainty and Financial Conditions as Predictors of Economic Activity

As a warm-up exercise, we first explore the relative roles of uncertainty and financial conditions as predictors of the near-term course in economic activity. Specifically, letting Y_t denote a monthly measure of economic activity, we estimate the following forecasting regression:

$$\Delta_h Y_{t+h} = \alpha + \beta_1 \sigma_t + \beta_2 \text{EBP}_t + \sum_{i=1}^{h+1} \gamma_i \Delta Y_{t-i} + \epsilon_{t+h}, \tag{1}$$

where $\Delta_h Y_{t+h} \equiv \frac{1200}{h+1} \ln \left(\frac{Y_{t+h}}{Y_{t-1}} \right)$ and $h \geq 0$ is the forecast horizon ($\Delta_0 \equiv \Delta$); σ_t denotes one of our six uncertainty proxies in month t; EBP_t is the excess bond premium in the same month; and ϵ_{t+h} is the forecast error.

For each of the six uncertainty proxies, we estimate the forecasting regression (1) separately by OLS. Measures of monthly economic activity considered include manufacturing industrial production index and private (nonfarm) payroll employment. To facilitate the comparison of the predictive power of economic uncertainty and financial conditions, we report the standardized estimates of the coefficients β_1 and β_2. The results for the forecast horizon of 3 months are tabulated in Table 2, while those for the 12-month horizon are shown in Table 3.

According to Table 2, the predictive content of various uncertainty measures for economic activity is fairly uneven at the 3-month horizon. While increases in the realized stock market volatility are associated with statistically and economically significant slowdown in the growth of real industrial output and employment, the information content of the IVOL and VXO uncertainty proxies is quite limited. Similarly, the BBD economic policy uncertainty index appears to be uninformative about the near-term course of economic activity, conditional on the EBP. The JLN and BES uncertainty measures, by contrast, are strong predictors of the growth in both real industrial output and employment over the 3-month horizon.

In comparison with these uncertainty measures, the EBP appears to be a considerably more reliable predictor of near-term economic developments. In all specifications, the estimated coefficients imply an economically and statistically significant negative relationship between the tightness of financial conditions and subsequent economic activity. For example, using a coefficient estimate of 0.40, a value in the range of the central tendency of the point estimates reported in panel (a), an increase of 50 basis points in the EBP in month t—a move of about one standard deviation—implies

TABLE 2: Uncertainty, Financial Conditions, and Economic Activity
(3-month Forecast Horizon)

Predictor	RVOL	IVOL	VXO	JLN	BBD	BES
(a) *Industrial Production*						
σ_t	−0.15**	−0.06	0.02	−0.34***	−0.08	−0.26***
	[2.51]	[1.20]	[0.03]	[4.09]	[1.27]	[3.95]
EBP_t	−0.31***	−0.38***	−0.46***	−0.30***	−0.42***	−0.40***
	[3.65]	[4.00]	[3.33]	[4.19]	[3.37]	[4.49]
Adj. R^2	0.36	0.35	0.45	0.41	0.45	0.41
(b) *Payroll Employment*						
σ_t	−0.12***	−0.09**	−0.05	−0.22***	−0.03	−0.19***
	[4.01]	[2.25]	[1.32]	[3.89]	[0.74]	[3.74]
EBP_t	−0.23***	−0.27***	−0.25***	−0.23***	−0.27***	−0.27***
	[5.84]	[4.26]	[3.86]	[4.27]	[3.61]	[4.14]
Adj. R^2	0.67	0.67	0.80	0.69	0.81	0.70

NOTE: The dependent variable in each specification is $\Delta_3 Y_{t+3}$, the annualized log-difference in the specified indicator of economic activity from month $t-1$ to month $t+3$. The entries in the rows of the table corresponding to σ_t denote the standardized estimates of the OLS coefficients associated with the specified uncertainty proxy in month t: RVOL = realized equity volatility (1973:M1–2015:M3, $T = 507$); IVOL = idiosyncratic equity volatility based on Gilchrist et al. (2014) (1973:M1–2015:M3, $T = 507$); VXO = option-implied volatility on the S&P 100 stock futures index (1986:M1–2015:M3, $T = 351$); JLN = uncertainty measure based on Jurado et al. (2015) (1973:M1–2015:M3, $T = 507$); BBD = uncertainty measure based on Baker et al. (2015) (1985:M1–2015:M3, $T = 363$); and BES = uncertainty measure based on Bachmann et al. (2013) (1973:M1–2011:M12, $T = 468$). The entries in the rows of the table corresponding to EBP_t denote the standardized estimates of the OLS coefficients associated with the EBP in month t. In addition to σ_t and EBP_t, each specification also includes a constant and lags $1, 2, \ldots, 4$ of ΔY_t (not reported). Absolute t-statistics reported in brackets are based on the heteroskedasticity- and autocorrelation-consistent asymptotic covariance matrix computed according to Newey and West (1987) with the automatic lag selection method of Newey and West (1994): * $p < .10$; ** $p < .05$; and *** $p < .01$.

a nearly 3 percentage points (annualized) drop in the growth rate of real industrial output over the following three months. In the labor market (panel (b)), such a tightening of financial conditions is estimated to reduce employment growth by more than one-half of a percentage point over the same horizon.

The uneven forecasting performance of the uncertainty indicators is even more evident at longer forecast horizons (Table 3). Conditional on the EBP, uncertainty proxies based on stock market data (RVOL, IVOL, and VXO) have no predictive power for the growth of industrial production one-year ahead (panel (a)); and the same is true of the BBD economic policy uncertainty index. Once the state of current financial market conditions is taken into account, it is only the JLN and BES uncertainty measures that are informative about the trajectory of real industrial output over the next 12 months.

A similar picture emerges when we turn to the labor market (panel (b)). The RVOL, IVOL, and VXO uncertainty measures have essentially no marginal predictive power for the year-ahead employment growth, nor does the BBD uncertainty measure appear to be a useful indicator of future labor market developments. Again, only the JLN and BES uncertainty measures help predict

TABLE 3: Uncertainty, Financial Conditions, and Economic Activity
(12-month Forecast Horizon)

Predictor	RVOL	IVOL	VXO	JLN	BBD	BES
(a) *Industrial Production*						
σ_t	-0.08	-0.01	0.05	-0.62^{***}	0.01	-0.32^{***}
	[1.25]	[0.06]	[0.46]	[5.51]	[0.10]	[3.16]
EBP_t	-0.37^{***}	-0.41^{***}	-0.52^{***}	-0.28^{***}	-0.49^{***}	-0.39^{***}
	[2.89]	[3.34]	[2.77]	[2.78]	[3.09]	[3.84]
Adj. R^2	0.20	0.19	0.24	0.39	0.23	0.28
(b) *Payroll Employment*						
σ_t	-0.10^{*}	-0.13	-0.00	-0.34^{***}	0.07	-0.35^{***}
	[1.83]	[1.39]	[0.01]	[4.03]	[1.27]	[3.59]
EBP_t	-0.36^{***}	-0.38^{***}	-0.36^{***}	-0.31^{***}	-0.39^{***}	-0.37^{***}
	[3.77]	[4.13]	[3.63]	[3.79]	[4.24]	[4.45]
Adj. R^2	0.45	0.46	0.61	0.52	0.61	0.54

NOTE: The dependent variable in each specification is $\Delta_{12}Y_{t+12}$, the annualized log-difference in the specified indicator of economic activity from month $t-1$ to month $t+12$. The entries in the rows of the table corresponding to σ_t denote the standardized estimates of the OLS coefficients associated with the specified uncertainty proxy in month t: RVOL = realized equity volatility (1973:M1–2015:M3, $T = 507$); IVOL = idiosyncratic equity volatility based on Gilchrist et al. (2014) (1973:M1–2015:M3, $T = 507$); VXO = option-implied volatility on the S&P 100 stock futures index (1986:M1–2015:M3, $T = 351$); JLN = uncertainty measure based on Jurado et al. (2015) (1973:M1–2015:M3, $T = 507$); BBD = uncertainty measure based on Baker et al. (2015) (1985:M1–2015:M3, $T = 363$); and BES = uncertainty measure based on Bachmann et al. (2013) (1973:M1–2011:M12, $T = 468$). The entries in the rows of the table corresponding to EBP_t denote the standardized estimates of the OLS coefficients associated with the EBP in month t. In addition to σ_t and EBP_t, each specification also includes a constant and lags $1, 2, \ldots, 13$ of ΔY_t (not reported). Absolute t-statistics reported in brackets are based on the heteroskedasticity- and autocorrelation-consistent asymptotic covariance matrix computed according to Newey and West (1987) with the automatic lag selection method of Newey and West (1994): * $p < .10$; ** $p < .05$; and *** $p < .01$.

employment growth over the 12-month horizon. In contrast, movements in the EBP continue to provide unambiguous and informative signals about the evolution of the year-ahead economic outlook, with a tightening of financial conditions portending a marked deceleration in real industrial output and a significant deterioration in labor market conditions.[10]

The results from the above forecasting exercises—which, of course, are completely silent on the causal relationship between uncertainty, financial conditions, and economic activity—are instructive for two reasons. First, they underscore the fact that measures of financial conditions based on corporate bond credit spreads are highly informative about the economic outlook. Second, although the information content of various uncertainty indicators is decidedly mixed, the available evidence nevertheless suggests that some of these indicators contain economically and statistically significant marginal predictive power for economic activity. In combination with the fact that episodes of

---

[10]As a robustness check, we also estimated forecasting regressions that in addition to the EBP and an uncertainty proxy also conditioned on the level of real risk-free interest rates and the slope of the yield curve (i.e., the term spread). The inclusion of these additional financial variables, however, yielded the same conclusions regarding the relative predictive power of the EBP and various uncertainty proxies.

financial distress are closely associated with periods of heightened economic uncertainty and that theoretical mechanisms based on frictions in financial markets imply an important interaction between changes in financial conditions and fluctuations in uncertainty, a natural question raised by this evidence concerns the relative importance of financial and uncertainty shocks in business cycle fluctuations. To answer this question empirically, however, one has to take a stand on the joint identification of these two types of shocks, the subject of the remainder of the paper.

3 Identifying Uncertainty and Financial Shocks

To identify uncertainty and financial shocks, we employ the penalty function approach (PFA) proposed initially by Faust (1998) and Uhlig (2005) in the context of the VAR-based identification of monetary policy shocks. This approach was later extended by Mountford and Uhlig (2009) to jointly identify multiple structural disturbances. In brief, the PFA selects a structural VAR model by maximizing a criterion function subject to inequality constraints. The criterion function consists of the sum of impulse response functions (IRFs) of selected variables from horizon 0 to horizon H, while the inequality constraints correspond to sign restrictions on these IRFs. In this section, we first provide a general formulation of the PFA. We then discuss the rationale underlying our two identification schemes—that is, the choice of the penalty functions—and the estimation details.

3.1 The SVAR and the Penalty Function

Consider the following SVAR:

$$\mathbf{y}_t'\mathbf{A}_0 = \sum_{i=1}^{p} \mathbf{y}_{t-i}'\mathbf{A}_i + \mathbf{c} + \boldsymbol{\epsilon}_t'; \quad t = 1,\dots,T, \tag{2}$$

where $\mathbf{y}_t$ is an $n \times 1$ vector of endogenous variables, $\boldsymbol{\epsilon}_t$ is an $n \times 1$ vector of structural shocks, $\mathbf{A}_i$, $i = 1,\dots,p$, is an $n \times n$ matrix of structural parameters with $\mathbf{A}_0$ invertible, $\mathbf{c}$ is a $1 \times n$ vector of parameters, p is the lag length, and T is the sample size. Conditional on past information and the initial conditions $\mathbf{y}_0,\dots,\mathbf{y}_{1-p}$, the vector of structural shocks $\boldsymbol{\epsilon}_t$ is assumed to be Gaussian with mean zero and covariance matrix $\mathbf{I}_n$, the $n \times n$ identity matrix.

The SVAR model in equation (2) can be written more compactly as

$$\mathbf{y}_t'\mathbf{A}_0 = \mathbf{x}_t'\mathbf{A}_+ + \boldsymbol{\epsilon}_t',$$

where $\mathbf{A}_+' = \begin{bmatrix} \mathbf{A}_1' \dots \mathbf{A}_p' & \mathbf{c}' \end{bmatrix}$ and $\mathbf{x}_t' = \begin{bmatrix} \mathbf{y}_{t-1}' \dots \mathbf{y}_{t-p}' & \mathbf{1} \end{bmatrix}$. The dimension of $\mathbf{A}_+$ is $m \times n$, where $m = np + 1$, and the elements of matrices $\mathbf{A}_0$ and $\mathbf{A}_+$ correspond to the structural parameters of the VAR system. The reduced-form representation of the VAR is given by

$$\mathbf{y}_t' = \mathbf{x}_t'\mathbf{B} + \mathbf{u}_t',$$

where $\mathbf{B} = \mathbf{A}_+\mathbf{A}_0^{-1}$, $\mathbf{u}_t' = \boldsymbol{\epsilon}_t'\mathbf{A}_0^{-1}$, and $\mathbb{E}\big[\mathbf{u}_t\mathbf{u}_t'\big] = \big(\mathbf{A}_0\mathbf{A}_0'\big)^{-1} \equiv \boldsymbol{\Omega}$; the matrices $\mathbf{B}$ and $\boldsymbol{\Omega}$ are the reduced-form parameters.

The impulse response functions are defined as follows. Let $\{\mathbf{A}_0, \mathbf{A}_+\}$ represent arbitrary structural parameters. Then, the IRF of the i-th variable to the j-th structural shock at a finite horizon h, denoted by $\mathbf{L}_h(\mathbf{A}_0, \mathbf{A}_+)_{ij}$, corresponds to the element in row i and column j of the matrix $\big[\mathbf{A}_0^{-1}\mathbf{J}'\mathbf{F}^h\mathbf{J}\big]'$, where

$$\mathbf{F} = \begin{bmatrix} \mathbf{A}_1\mathbf{A}_0^{-1} & \mathbf{I}_n & \cdots & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{A}_{p-1}\mathbf{A}_0^{-1} & \mathbf{0} & \cdots & \mathbf{I}_n \\ \mathbf{A}_p\mathbf{A}_0^{-1} & \mathbf{0} & \cdots & \mathbf{0} \end{bmatrix} \quad \text{and} \quad \mathbf{J} = \begin{bmatrix} \mathbf{I}_n \\ \mathbf{0} \\ \vdots \\ \mathbf{0} \end{bmatrix}.$$

Note that the matrix of IRFs upon impact is given by $\mathbf{L}_0\big(\mathbf{A}_0, \mathbf{A}_+\big) = \mathbf{A}_0^{-1}$. As in Uhlig (2005), we characterize the set of all possible IRFs using an $n \times n$ orthonormal matrix $\mathbf{Q} \in \mathscr{O}(n)$, where $\mathscr{O}(n)$ denotes the set of all orthonormal $n \times n$ matrices. To see this, let $\mathbf{T}$ denote the lower triangular matrix from the Cholesky factorization of $\boldsymbol{\Omega}$. Then for any orthonormal matrix $\mathbf{Q}$, the matrix $\tilde{\mathbf{A}}_0^{-1} = \mathbf{TQ}$ is also a decomposition of $\boldsymbol{\Omega}$ that satisfies $\big[\tilde{\mathbf{A}}_0\tilde{\mathbf{A}}_0'\big]^{-1} = \boldsymbol{\Omega}$. Identification of the SVAR thus amounts to specifying a set of restrictions on the matrix $\mathbf{Q}$. For instance, $\mathbf{Q} = \mathbf{I}_n$ imposes identification based on the recursive ordering of the VAR—the widely used Cholesky decomposition—while sign restrictions on the IRFs involve specifying a set of admissible $\mathbf{Q}$ matrices.

It is worth emphasizing that our identification strategy does not identify all n structural shocks—that is, the entire $\mathbf{Q}$ matrix. Rather, we identify a subset $k \leq n$ of shocks, represented by $\mathbf{q}_j = \mathbf{Q}\mathbf{e}_j$, $j = 1, ..., k$, where $\mathbf{e}_j$ denotes the j-th column of $\mathbf{I}_n$. Specifically, let $\{\mathbf{A}_0, \mathbf{A}_+\}$ be any draw of the structural parameters and consider a case where the identification of the j-th structural shock restricts the IRF of a set of variables indexed by $I_j^+ \subset \{0, 1, \ldots, n\}$ to be positive and the IRF of a set of variables indexed by $I_j^- \subset \{0, 1, \ldots, n\}$ to be negative. Furthermore, assume that the restrictions on variable i are enforced for $H \geq 0$ periods. The identification of $\mathbf{q}_j$ then amounts to solving the following optimization problem:

$$\mathbf{q}_j^* = \underset{\mathbf{q}_j}{\arg\min} \; \Psi(\mathbf{q}_j) \tag{3}$$

subject to

$$\mathbf{e}_i'\mathbf{L}_h(\mathbf{T}^{-1}, \mathbf{BT}^{-1})\mathbf{q}_j > 0, \quad i \in I_j^+ \text{ and } h = 0, \ldots, H; \tag{4}$$

$$\mathbf{e}_i'\mathbf{L}_h(\mathbf{T}^{-1}, \mathbf{BT}^{-1})\mathbf{q}_j < 0, \quad i \in I_j^- \text{ and } h = 0, \ldots, H; \tag{5}$$

$$\mathbf{Q}_{j-1}^{*\prime}\mathbf{q}_j = 0, \tag{6}$$

where

$$\Psi(\mathbf{q}_j) = \sum_{i \in I_j^+} \sum_{h=0}^{H} \left(-\frac{\mathbf{e}_i'\mathbf{L}_h(\mathbf{T}^{-1}, \mathbf{BT}^{-1})\mathbf{q}_j}{\omega_i} \right) + \sum_{i \in I_j^-} \sum_{h=0}^{H} \left(\frac{\mathbf{e}_i'\mathbf{L}_h(\mathbf{T}^{-1}, \mathbf{BT}^{-1})\mathbf{q}_j}{\omega_i} \right), \tag{7}$$

ω_i is the standard deviation of variable i, and $\mathbf{Q}^*_{j-1} = \begin{bmatrix} \mathbf{q}^*_1 \dots \mathbf{q}^*_{j-1} \end{bmatrix}$, for $j = 1, \dots, n$.[11]

In line with the existing literature, our characterization of the penalty function given by equation (7) assumes that the vector $\mathbf{q}_j$ rotates the IRFs associated with the Cholesky factor matrix $\mathbf{T}$. As in Uhlig (2005) and Mountford and Uhlig (2009), the constraints (4) and (5) correspond to sign restrictions on the IRFs that enter the penalty function $\Psi(\mathbf{q}_j)$. Note that the PFA selects a single rotation matrix $\mathbf{Q}^*$ for each draw of the structural parameters $\{\mathbf{A}_0, \mathbf{A}_+\}$, the same as in the standard point identification. However, the PFA differs from the standard sign restriction approach because the IRFs corresponding to each draw of the structural parameters $\{\mathbf{A}_0, \mathbf{A}_+\}$ are computed using the rotation matrix $\mathbf{Q}^*$ that minimizes the penalty function (7). The constraints (4) and (5) do not identify a set of structural models—that is, a set of $\mathbf{Q}$ matrices—rather, they define a set of admissible rotation matrices from which the matrix $\mathbf{Q}^*$ is selected.[12] In our implementation of the PFA, however, the sign restrictions are never violated, and the rotation matrix $\mathbf{Q}^*$ always lies in the interior of the admissible set.

Following Mountford and Uhlig (2009), we jointly identify multiple structural shocks sequentially by specifying a penalty function (7) for each shock and imposing—via the constraint (6) in the optimization problem (3)—that shock j is orthogonal to shocks $1, \dots, j - 1$. This sequential approach is reminiscent of a recursive ordering implicit in the Cholesky decomposition—in fact, this approach returns a Cholesky factorization of $\mathbf{\Omega}$ if the penalty function that identifies shock j contains only the impact response ($H = 0$) of variable j, for $j = 1, \dots, n$. In all other cases, the sequential identification of the shocks using the PFA does not impose any zero restrictions on the structural parameters $\{\mathbf{A}_0, \mathbf{A}_+\}$ or on the IRFs at any horizon.

This identification strategy, however, is not invariant to the ordering of the shocks. Next we describe the two identification schemes used in our analysis, which share the same penalty function and differ only in the ordering of the uncertainty and financial shocks. For the purpose of describing the two identification schemes, it suffices to say that without loss of generality, we order the EBP and an uncertainty measure first and second, respectively, in the vector of the endogenous variables $\mathbf{y}_t$.

3.2 Identification and Estimation

Both of our identification schemes involve two steps. In the baseline identification scheme, the first step identifies the uncertainty shock as an innovation that generates the *largest increase* in a measure of uncertainty for the first six months. The penalty function associated with this shock is given by

$$\Psi(\mathbf{q}_1) = \sum_{h=0}^{5} \left(-\frac{\mathbf{e}'_1 \mathbf{L}_h(\mathbf{T}^{-1}, \mathbf{B}\mathbf{T}^{-1})\mathbf{q}_1}{\omega_1} \right),$$

---

[11]We follow the convention by letting $\mathbf{Q}^*_0$ equal the $n \times n$ null matrix; to obtain ω_i, we compute the standard deviation of the OLS residuals associated with the i-th variable.

[12]This identification strategy differs from the pure sign restriction identification approach, in that both of our identification schemes identify a single structural VAR specification, rather than a set of models (Caldara and Kamps, 2012; Arias et al., 2013).

with

$$\mathbf{e}_1' \mathbf{L}_h(\mathbf{T}^{-1}, \mathbf{BT}^{-1})\mathbf{q}_1 > 0, \quad h = 0, \ldots, 5,$$

where $j = 1$ because we identify the first shock in the system; $i = 1$ because the uncertainty measure is the first variable in the system; $I_1^+ = \{1\}$ and $I_1^- = \emptyset$ because we only impose positive restrictions on the uncertainty measure; and $H = 5$ because we restrict the IRFs of the uncertainty measure for the first six months (in our notation the impact response occurs in period 0).[13]

The second step in the scheme identifies financial shocks. Specifically, a financial shock is an innovation that generates the *largest increase* in the EBP for the first six months and is orthogonal to the uncertainty disturbance identified by the first step. The penalty function associated with this shock is given by

$$\Psi(\mathbf{q}_2) = \sum_{h=0}^{5} \left(-\frac{\mathbf{e}_2' \mathbf{L}_h(\mathbf{T}^{-1}, \mathbf{BT}^{-1})\mathbf{q}_2}{\omega_2} \right),$$

with

$$\begin{aligned}
\mathbf{e}_2' \mathbf{L}_h(\mathbf{T}^{-1}, \mathbf{BT}^{-1})\mathbf{q}_2 &> 0, \quad h = 0, \ldots, 5; \\
\mathbf{Q}_1^{*\prime} \mathbf{q}_2 &= 0,
\end{aligned}$$

where $j = 2$ because we are identifying the second shock and $i = 2$ because the EBP is the second variable in the VAR.

Implicit in this identification scheme—which we call the σ–EBP identification—is the argument that fluctuations in economic uncertainty are driven mainly by uncertainty shocks, while unanticipated worsening in financial conditions is due primarily to an adverse financial shock. Moreover, such shocks elicit a persistent increase in their corresponding endogenous variable over the near-term horizon, rather than just a maximal impact response. These identifying assumptions do not rule out the possibility that financial conditions might react contemporaneously to a change in economic uncertainty induced by an uncertainty shock; by the same token, macroeconomic uncertainty is allowed to change immediately in response to a financial shock.

Although more general than the identification strategy based on the recursive ordering of the VAR system, the σ–EBP identification scheme still imposes a timing restriction—namely, the optimization problem that identifies the financial shock is solved conditional on solving the optimization that identifies the uncertainty shock. Given the close relationship between changes in financial conditions and swings in economic uncertainty, this sequential ordering may lead to a concern that the identified uncertainty shocks are to some extent contaminated by financial shocks. This concern may be especially relevant in the case of uncertainty proxies based solely on financial asset prices (i.e., RVOL, IVOL, and VXO), movements in which reflect the confluence of fluctuations in the underlying uncertainty and changes in risk aversion.

To take into account this possibility, our second identification scheme, which we refer to as

---

[13]All the results reported in the paper were qualitatively and quantitatively very similar if uncertainty and financial shocks were identified using a longer response horizon.

the EBP-σ identification, reverses the ordering of the two optimization problems. In other words, we first identify the financial shock as an innovation that generates the largest increase in the EBP—a persistent tightening of financial conditions—for the first six months. In the second step, an uncertainty shock, orthogonal to the financial disturbance implied by the first step, is identified as a shock that induces the largest increase in an uncertainty measure over the same horizon. We acknowledge that neither scheme fully resolves the difficult problem of how to identify these two types of shocks in a VAR context. However, in the absence of valid external instruments, we view the two approaches as providing useful bounds on the role of uncertainty and financial shocks in business cycle fluctuations.

In spirit, our implementation of the PFA is similar to the identification strategy used by Uhlig (2003), Barsky and Sims (2011), and Kurmann and Otrok (2013), all of whom identify structural shocks by maximizing—over a pre-specified forecast horizon—the shock's contribution to the forecast error variance of a given variable. Our identification schemes, in contrast, identify shocks by maximizing the impulse response of a given variable over a pre-specified horizon. We chose this approach because it implies that the identified financial shocks generate a persistent increase in the EBP—a prolonged period of financial distress—while uncertainty shocks lead to a persistent increase in an uncertainty proxy; that is, a period of heightened economic uncertainty, rather than just a one-off spike in volatility. Selecting shocks that maximize the forecast error variance of these two variables, by contrast, does not guarantee that their IRFs will not switch signs over the forecast horizon. However, the results reported below indicate that the two shocks identified using the PFA also explain a vast majority of the forecast error variance of their respective variables at business cycle frequencies, which suggests that these two approaches are unlikely to yield very different conclusions.

To implement the two identification schemes, we employ Bayesian estimation techniques. Our monthly VAR specification consists of 10 endogenous variables: (1) an uncertainty proxy; (2) the EBP; (3) the log-difference of manufacturing industrial production index; (4) the log-difference of private (nonfarm) payroll employment; (5) the log-difference of real personal consumption expenditures (PCE); (6) the log-difference of the PCE price deflator; (7) the nominal 2-year Treasury yield; (8) the nominal 10-year Treasury yield; (9) the value-weighted total stock market (log) return; and (10) the log-difference of the S&P Goldman Sachs Commodity Index. We impose a Minnesota prior on the reduced-form VAR parameters by using dummy observations (Del Negro and Schorfheide, 2011) and select the hyper-parameters that govern their prior distributions and the VAR lag length p by maximizing the marginal data density; to perform this optimization, we use the CMA-ES evolutionary algorithm proposed by Hansen et al. (2003). The resulting specification, which includes a constant, is estimated over the 1975:M1–2015:M3 period using six lags of the endogenous variables.[14]

---

[14]Details about the prior specification are provided in Appendix B. We use the first two years of the sample (1973:M1–1974:M12) as a training sample for the Minnesota prior. All the results reported in the paper are based on 50,000 draws from the posterior distribution of the structural parameters, where the first 10,000 draws were used as a burn-in period.

4 Economic Implications of Financial and Uncertainty Shocks

This section presents our main results. In presenting the results, we adopt the following exposition scheme, which is best viewed in color. Specifically, the results based on the σ–EBP identification use a green-based color motif, while the results based on the EBP–σ identification of these two shocks use an orange-based color motif.

The solid lines in panel (a) of Figure 3 show the median IRFs of the six uncertainty proxies to their own shocks under the σ–EBP identification scheme, while the shaded bands represent the corresponding 90-percent pointwise credible bands. Consistent with our identifying assumption that uncertainty shocks should elicit more than a one-off jump in uncertainty, the identified shocks in all cases induce a fairly persistent rise in their corresponding uncertainty proxy. With the exception of the JLN measure, which exhibits a hump-shaped response with a notably greater persistence, the responses of other proxies peak upon the impact of the shock, which then dies out within about 24 months.

The impact of these shocks on the EBP—our measure of broad financial conditions—is shown in panel (b) of Figure 3. In response to each uncertainty shock, the EBP jumps upon impact, indicating an immediate tightening of financial conditions. The deterioration in financial conditions is somewhat more severe in response to uncertainty shocks based on equity valuations (RVOL, IVOL, and VXO), though shocks to other uncertainty proxies also lead to a sizable increase in the EBP.

The macroeconomic effects of these uncertainty shocks are summarized in Figure 4.[15] As shown in panel (a), industrial production, an especially cyclically sensitive measure of economic activity, responds very quickly to an increase in economic uncertainty: real industrial output starts declining almost immediately and, depending on the uncertainty proxy used to identify the corresponding shock, bottoms out between 0.5 percent and 1 percent below trend about 14 months after the impact of the uncertainty shock. According to panel (b), the increase in economic uncertainty is also very bad news for the stock market: in almost every case, the persistent increase in uncertainty and the associated tightening of financial market conditions lead to a sharp and immediate drop in the broad stock market; the one exception to this pattern is the JLN uncertainty measure—the response of equity prices to the JLN uncertainty shock is not nearly as sharp and immediate as that implied by uncertainty shocks based on other proxies.

Figures 5 and 6 present the same information under the EBP–σ identification scheme. As shown in panel (a) of Figure 5, the IRFs of the different uncertainty proxies to their own shocks under this alternative identification scheme are very similar to those reported in the corresponding panel of Figure 3. However, as shown in panel (b), the effect of uncertainty shocks on financial conditions differs significantly under the EBP–σ identification scheme. In this case, adverse uncertainty shocks do not lead to a systematic deterioration in financial conditions. In fact, only uncertainty shocks
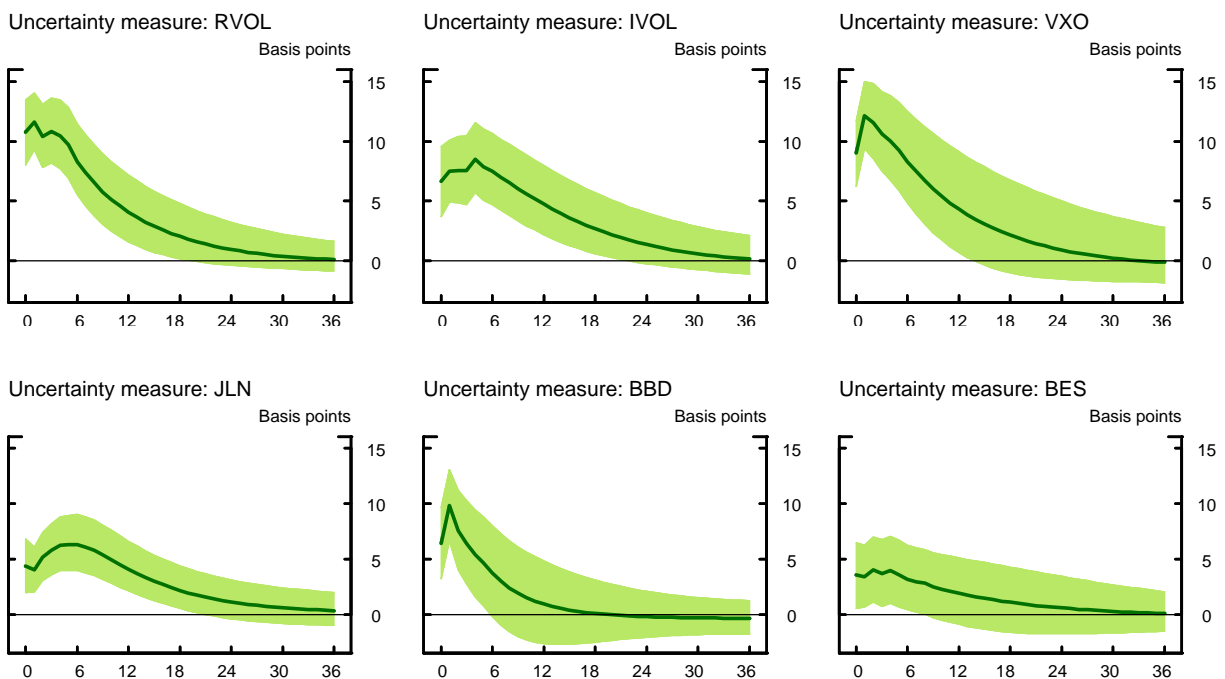
---

[15]To conserve space, we report only the IRFs of industrial production and the broad stock market. The responses of other endogenous variables to both uncertainty and financial shocks all have signs and patterns that are consistent with economic intuition and other related research.

FIGURE 3: Uncertainty Shocks Based on Different Uncertainty Proxies
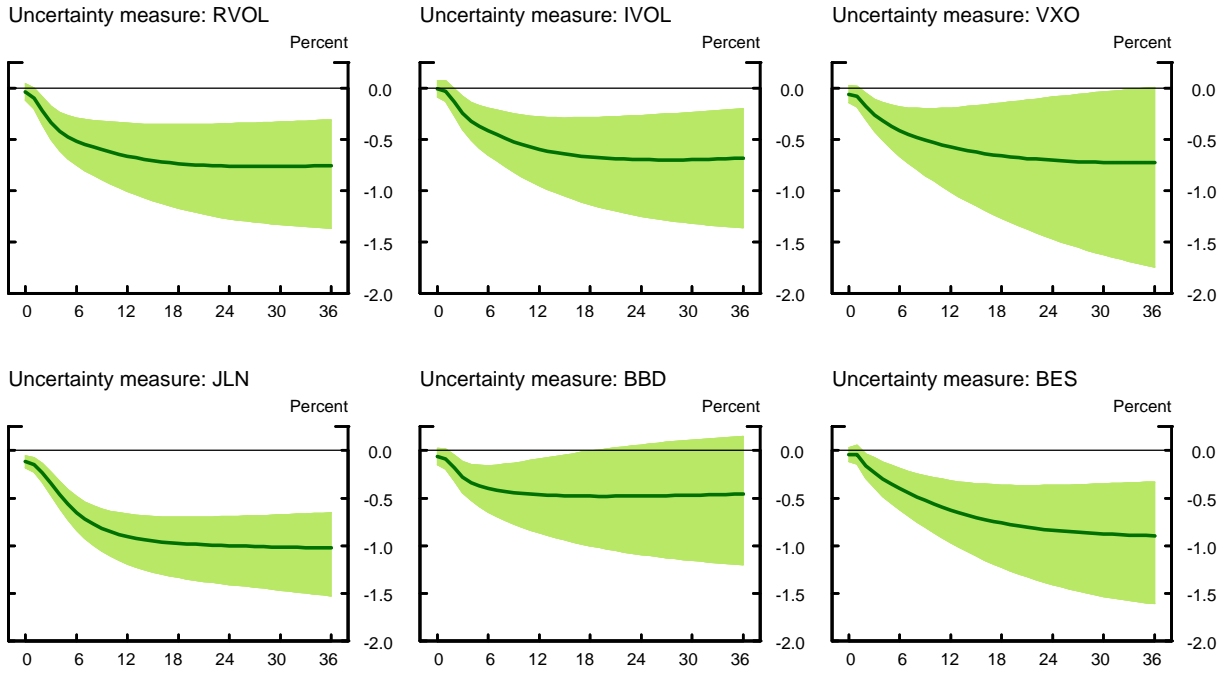(σ–EBP Identification)
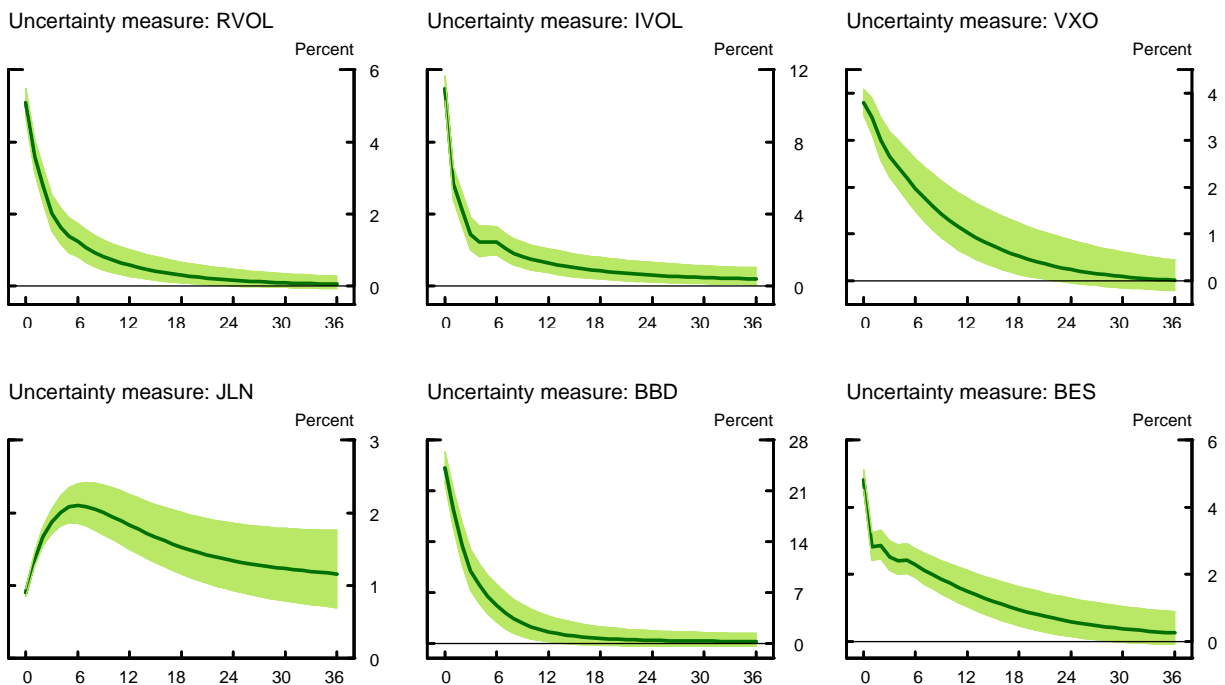
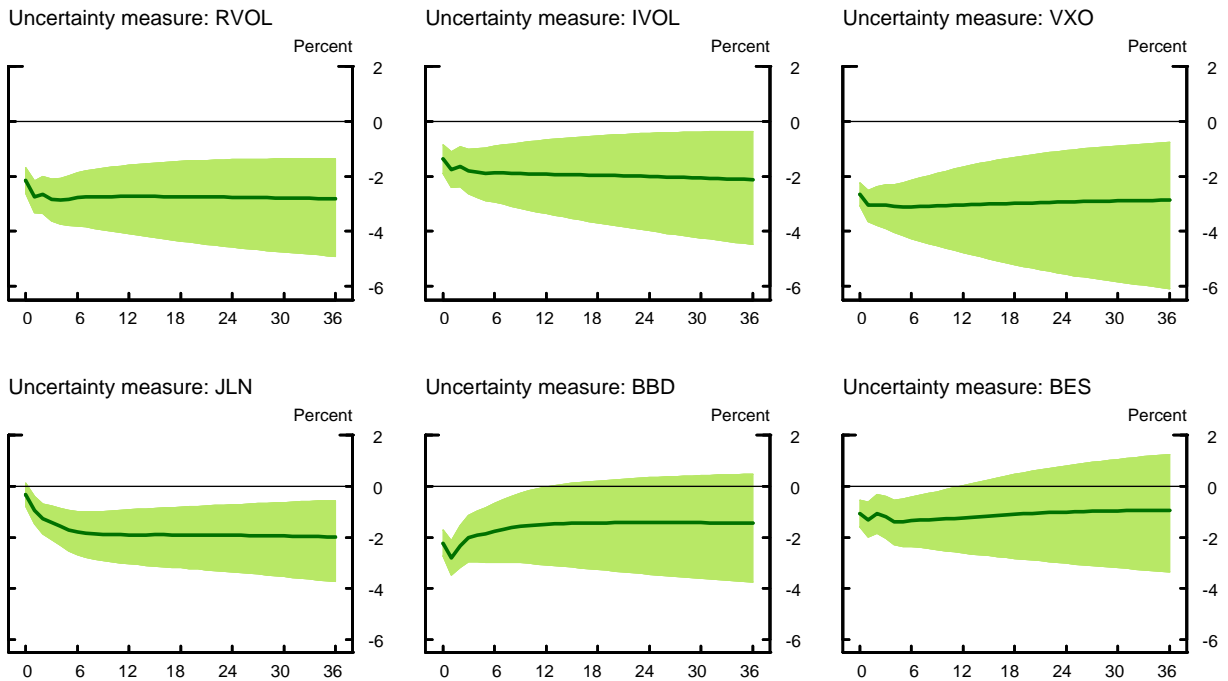(a) Response of different uncertainty proxies to their own shocks

(b) Response of the EBP to uncertainty shocks based on different uncertainty proxies

NOTE: The solid lines in panel (a) depict median responses of the specified uncertainty proxy to its own shock of 1 standard deviation, while those in panel (b) depict median responses of the EBP to the specified uncertainty shock of 1 standard deviation; the shaded bands represent the 90-percent pointwise credible sets. See the text and notes to Table 1 for details.

17

FIGURE 4: Economic Effects of Uncertainty Shocks Based on Different Uncertainty Proxies
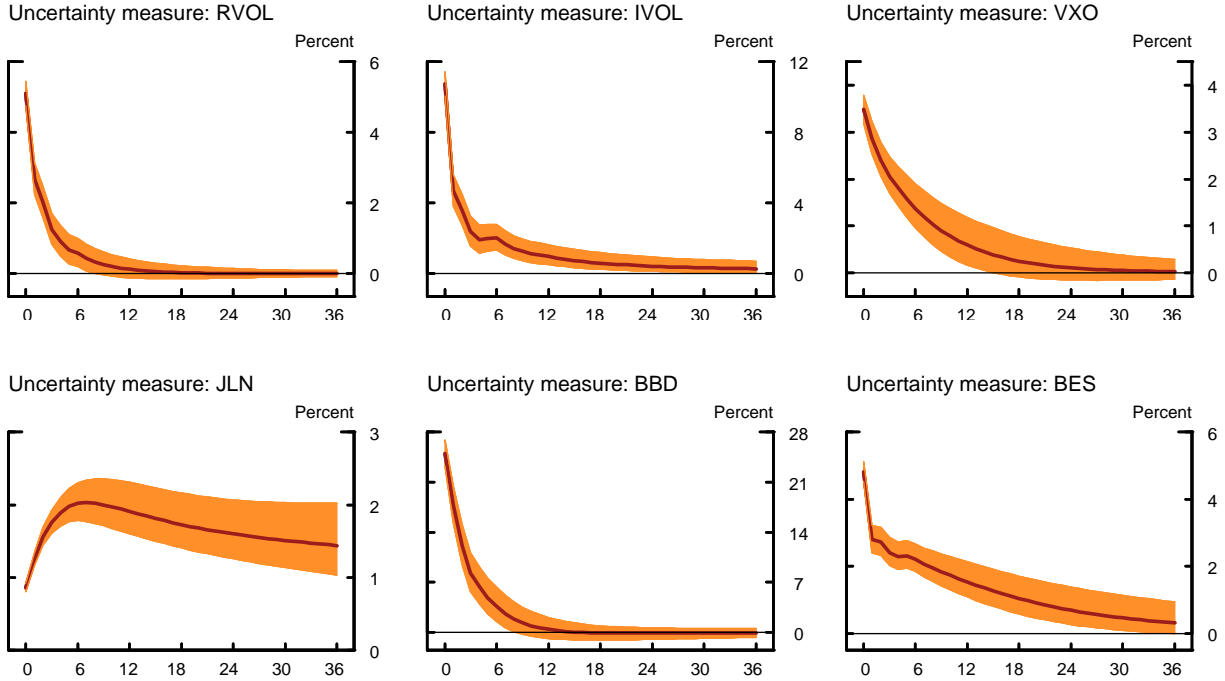(σ–EBP Identification)

(a) Response of industrial production to uncertainty shocks based on different uncertainty proxies
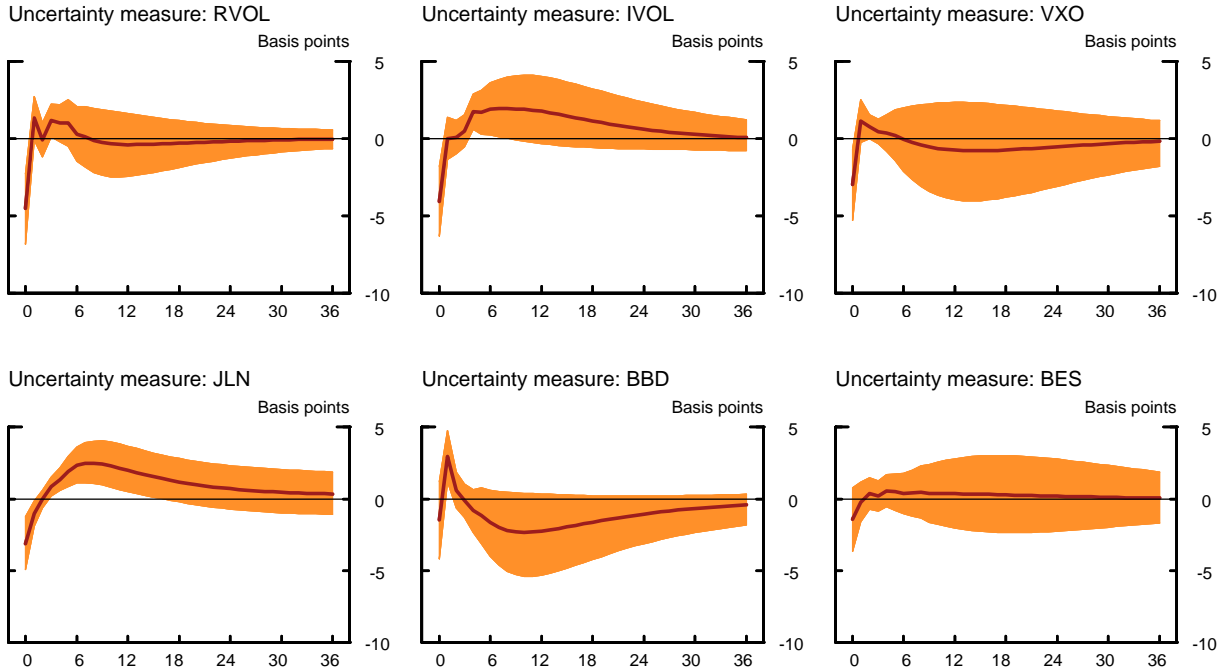

(b) Response of the stock market to uncertainty shocks based on different uncertainty proxies

NOTE: The solid lines in panel (a) depict median responses of industrial production to the specified uncertainty shock of 1 standard deviation, while those in panel (b) depict median responses of aggregate stock prices to the specified uncertainty shock of 1 standard deviation; the shaded bands represent the 90-percent pointwise credible sets. See the text and notes to Table 1 for details.

FIGURE 5: Uncertainty Shocks Based on Different Uncertainty Proxies
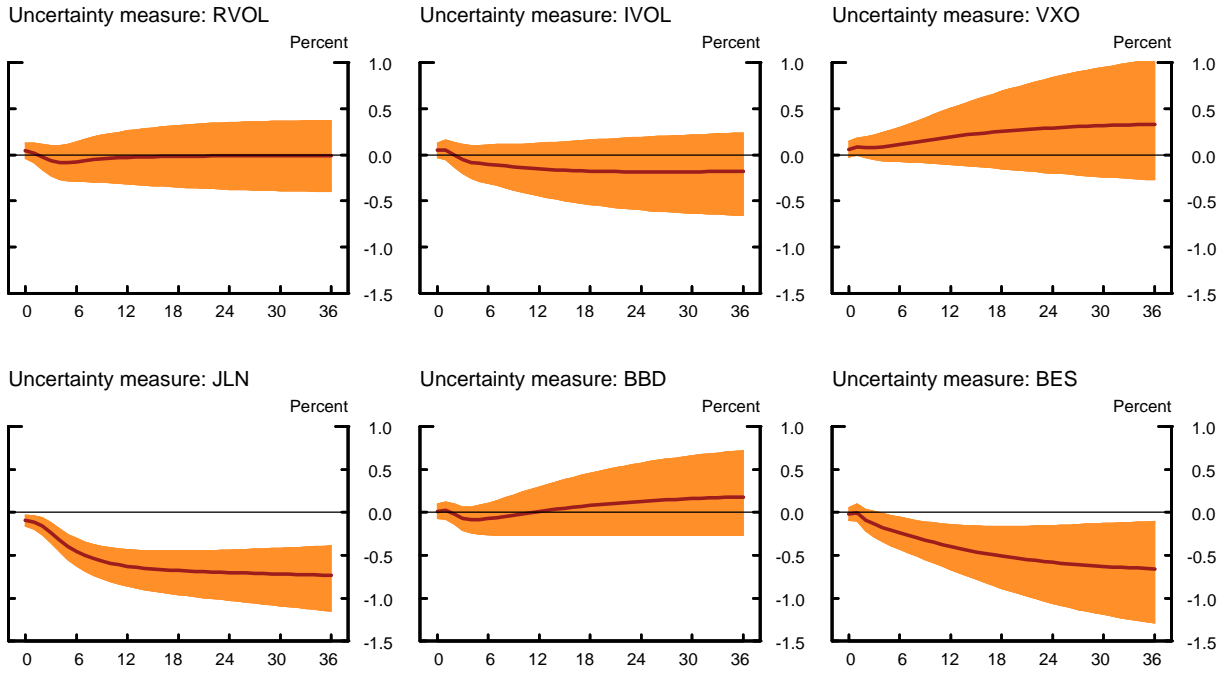(EBP-σ Identification)

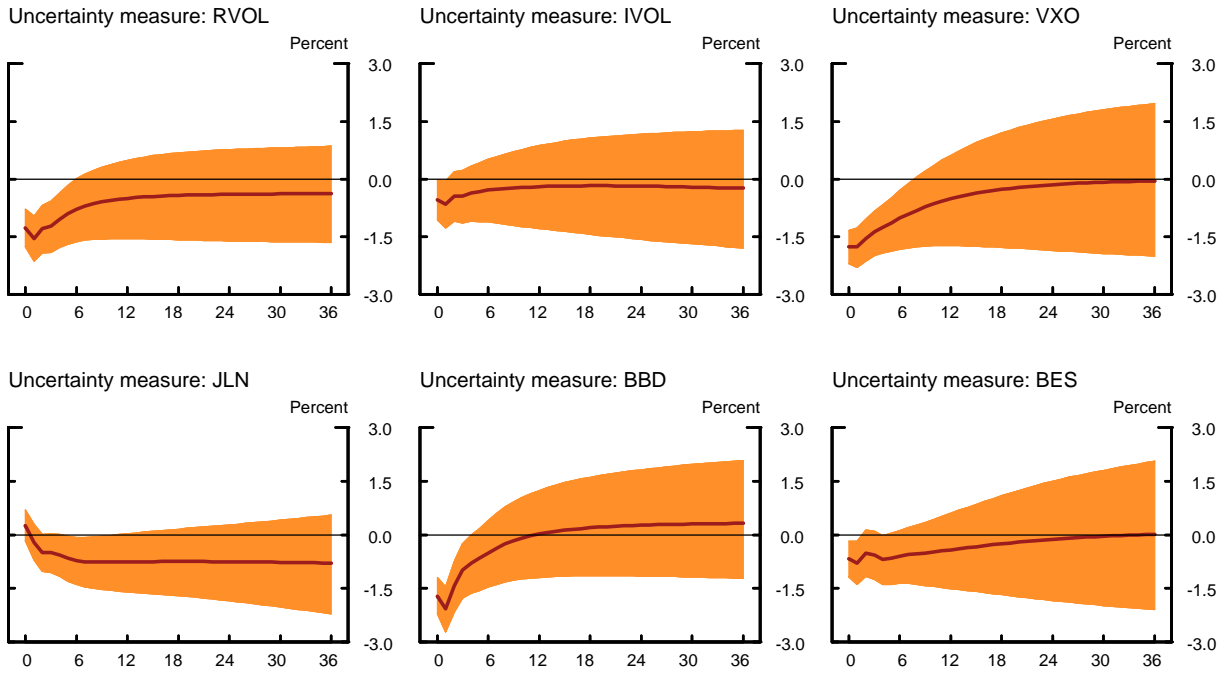(a) Response of different uncertainty proxies to their own shocks

(b) Response of the EBP to uncertainty shocks based on different uncertainty proxies

NOTE: The solid lines in panel (a) depict median responses of the specified uncertainty proxy to its own shock of 1 standard deviation, while those in panel (b) depict median responses of the EBP to the specified uncertainty shock of 1 standard deviation; the shaded bands represent the 90-percent pointwise credible sets. See the text and notes to Table 1 for details.

FIGURE 6: Economic Effects of Uncertainty Shocks Based on Different Uncertainty Proxies
(EBP-σ Identification)

(a) Response of industrial production to uncertainty shocks based on different uncertainty proxies

(b) Response of the stock market to uncertainty shocks based on different uncertainty proxies

NOTE: The solid lines in panel (a) depict median responses of industrial production to the specified uncertainty shock of 1 standard deviation, while those in panel (b) depict median responses of aggregate stock prices to the specified uncertainty shock of 1 standard deviation; the shaded bands represent the 90-percent pointwise credible sets. See the text and notes to Table 1 for details.

20

based on the JLN measure induce a statistically and economically significant rise in the EBP under this identification. For all other uncertainty proxies, increases in the EBP in response to different uncertainty shocks are quite small in economic terms and are also estimated imprecisely.[16]

This difference in the response of the EBP to uncertainty shocks has important macroeconomic implications. As shown in panel (a) of Figure 6, uncertainty shocks implied by the RVOL, IVOL, VXO, and BBD measures have no significant real effects. Only shocks based on the JLN and BES uncertainty measures have an economically and statistically meaningful impact on industrial production under the EBP–σ identification scheme. And even in those two cases, the effect of uncertainty shocks on real industrial output is appreciably smaller compared with that implied by the corresponding shocks under the σ–EBP identification (see panel (a) of Figure 4). These results suggest that financial market conditions are an important part of the mechanism through which uncertainty shocks affect the macroeconomy. And even though our two identification schemes do not impose any zero restrictions on the contemporaneous responses of financial conditions to economic uncertainty and vice versa, just reversing the order of the two optimization problems has a first-order effect on the macroeconomic relevance of uncertainty shocks.

This finding is particularly relevant for uncertainty proxies based on stock market data, where the sole effect of an uncertainty shock under the EBP–σ identification appears to be a short-lived decline in the stock market that has no consequences for real economic outcomes (see panel (b) of Figure 6). And while the JLN and BES uncertainty shocks both have real effects, the impact of the former shock on the stock market is more robust across the two identification schemes. This result may reflect the fact that the BES uncertainty proxy is based on the cross-sectional dispersion of indexes of expectations among survey participants and thus is more indicative of the degree of *disagreement* among the participants, rather than the actual forecast uncertainty, a point emphasized by D'Amico and Orphanides (2008). As a result, the remainder of the paper relies solely on the JLN measure of economic uncertainty. Under both of our identification schemes and consistent with the forecasting results reported in Section 2, this choice of the uncertainty proxy, in effect, gives economic uncertainty the maximum role in explaining business cycle fluctuations.

A useful way to judge the plausibility and economic importance of uncertainty shocks under our two identification schemes is depicted in Figure 7. The solid lines show the amount of variation in the forecast error variance in the JLN uncertainty proxy, the EBP, industrial production, and the broad stock market that is attributable to the JLN uncertainty shocks under the σ–EBP identification scheme; the dotted lines, in contrast, show the same information for the JLN uncertainty shocks implied by the EBP–σ identification scheme. Recall that in both schemes, the identification of uncertainty shocks involved selecting orthogonalized innovations in the JLN uncertainty proxy that maximized the response of this proxy over the first six months after the impact of the shock.

---

[16]The puzzling drop in the EBP that occurs upon impact of the different uncertainty shocks—especially those based on stock market data—is due in large part to the one-off spikes in financial market volatility, such as the stock market crash in October of 1987 and the "flash crash" in May of 2010. In those instances, stock market volatility increased sharply, but there was very little movement in credit spreads. In fact, when those observations are "dummied" out, the drop in the EBP upon the impact of uncertainty shocks is substantially attenuated.

FIGURE 7: Forecast Error Variance Decomposition of an Uncertainty Shock
(σ–EBP vs. EBP–σ Identification)
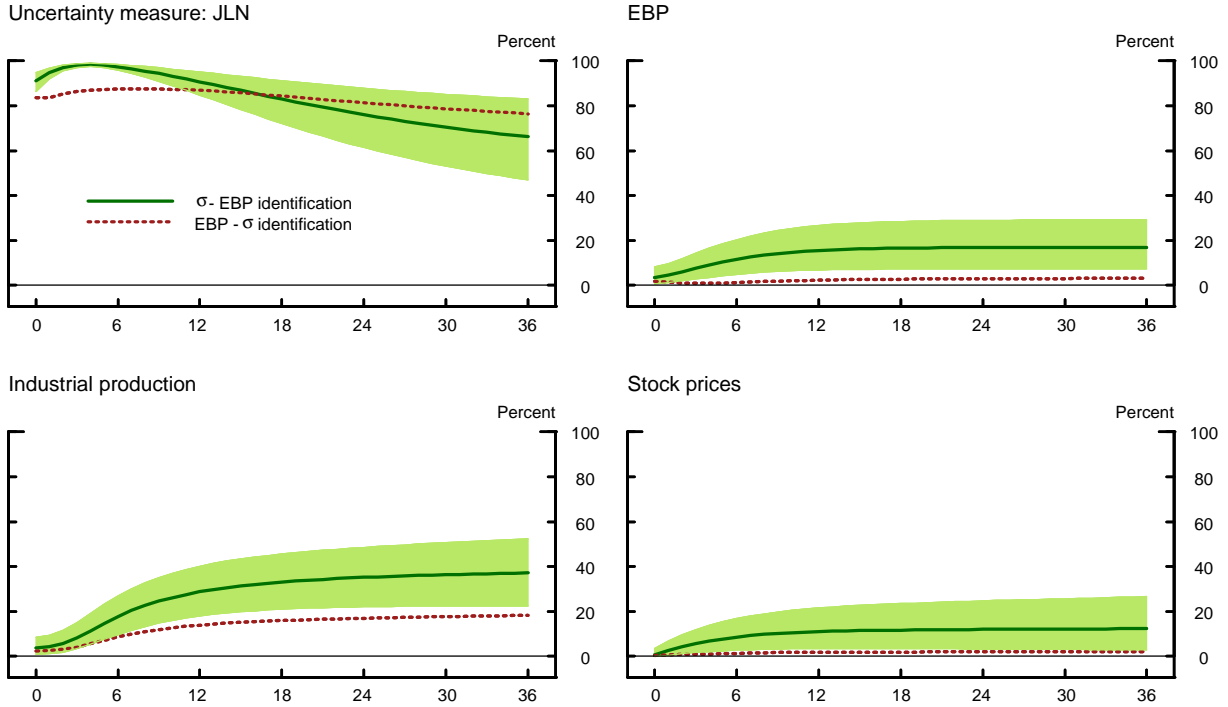
NOTE: The solid (dotted) line in each panel depicts the median estimate of the portion of the forecast error variance of a specified variable at different horizon that is attributable to a 1 standard deviation JLN uncertainty shock under the σ–EBP (EBP–σ) identification scheme; the shaded bands denote the 90-percent pointwise credible sets corresponding to the σ–EBP identification scheme.

And under both approaches, the identified uncertainty shocks account for the vast majority of the variation in the JLN measure at business cycle frequencies. This result is reassuring because it is consistent with our maintained assumption that fluctuations in economic uncertainty are due primarily to uncertainty shocks.

According to this metric, uncertainty shocks are a significant source of economic fluctuations—they are estimated to explain between 20 percent to 40 percent of the variation in industrial production at business cycle frequencies. Under the σ–EBP identification scheme, the JLN uncertainty shocks also explain an economically meaningful amount of the variation in the stock market and about one-fifth of the forecast error variance in the EBP. Under the EBP–σ identification scheme, by contrast, the JLN uncertainty shocks are completely uninformative about future swings in the EBP; similarly, their contribution to the forecast error variance of the stock market is indistinguishable from zero. Both of these results are consistent with the view that changes in financial market conditions are an important conduit through which uncertainty shocks affect the real economy and that uncertainty shocks are an important independent source of cyclical disturbances.

The macroeconomic implications of financial disturbances under both of our identification schemes are shown in Figure 8. According to the solid lines, an adverse financial shock under
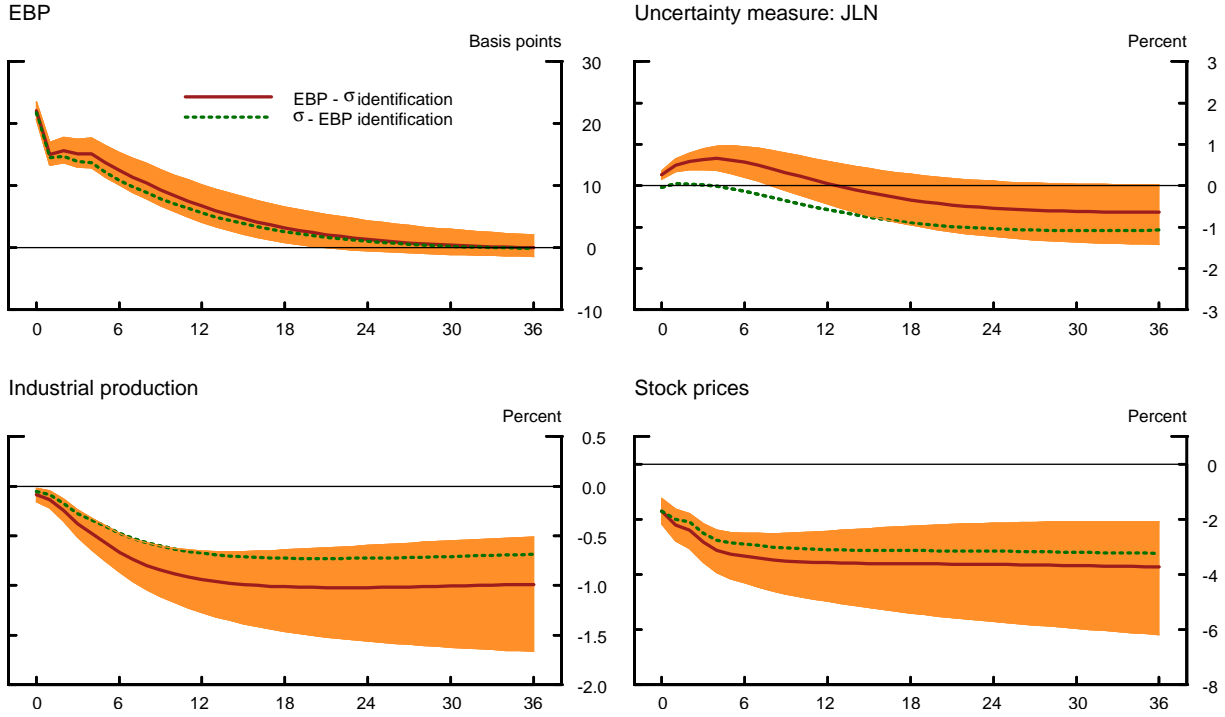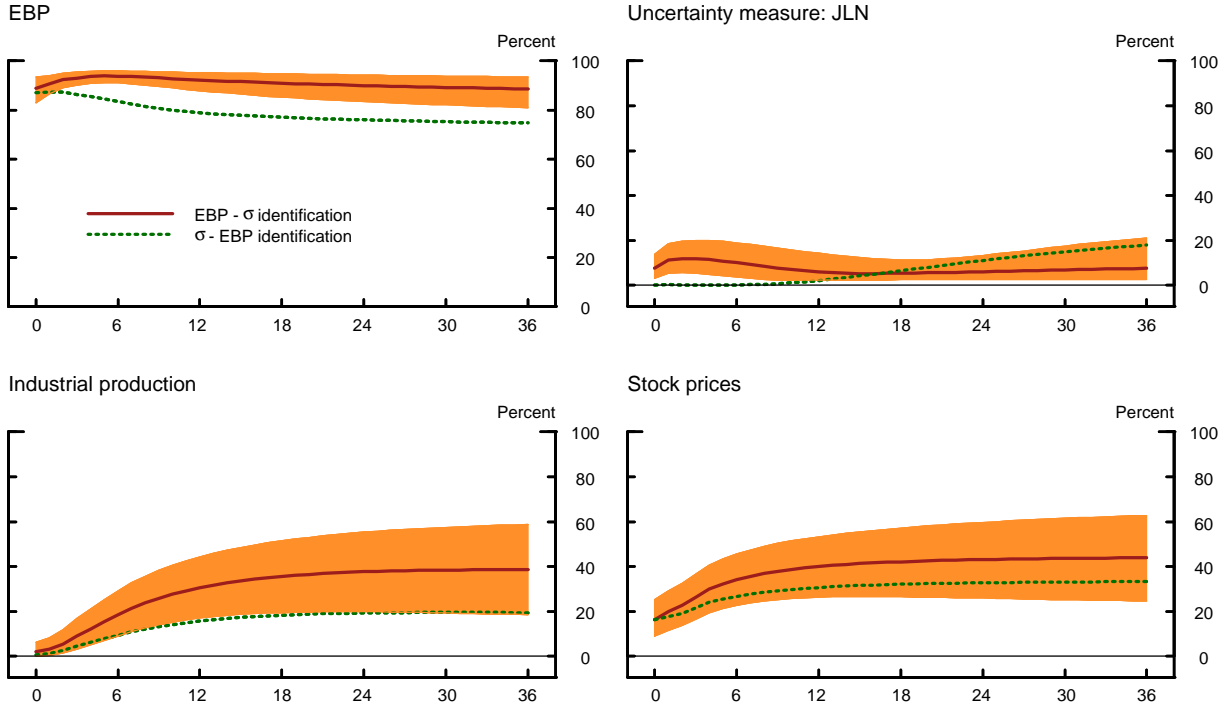
NOTE: The solid (dotted) line in each panel depicts the median response of a specified variable to a 1 standard deviation EBP shock under the EBP–σ (σ–EBP) identification scheme; the shaded bands denote the 90-percent pointwise credible sets corresponding to the EBP–σ identification scheme.

the EBP–σ identification scheme induces an economically significant and persistent increase in the EBP, a result consistent with our underlying identification strategy, which seeks to maximize the response of the EBP to its own shock. This significant tightening of financial conditions causes a mild increase in economic uncertainty and leads to a large and protracted decline in industrial production, as well as a sharp and immediate drop in the broad stock market.

Under the σ–EBP identification scheme, the dotted lines, the response of the EBP to the financial shock is virtually identical to that implied by the EBP–σ identification. However, the worsening of financial conditions has no effect on economic uncertainty under the σ–EBP identification scheme. Nevertheless, an adverse financial shock still results in a significant and persistent decline in real industrial output and a considerable drop in the stock market.

In Figure 9, we show the portion of the forecast error variance attributable to the financial shocks under our two identification schemes. In both cases, financial shocks account for the bulk of the variation in the EBP; at the same time, these shocks have only a limited impact on the JLN measure of economic uncertainty. Both of these findings are consistent with our assumptions that financial and uncertainty shocks—along with their potential interaction—are important independent sources of cyclical fluctuations. Indeed, according to our estimates, financial shocks explain 20 percent to 40 percent of the variation in real industrial output, the same amount as the JLN

FIGURE 9: Forecast Error Variance Decomposition of a Financial Shock
(EBP–σ vs. σ–EBP Identification)

NOTE: The solid (dotted) line in each panel depicts the median estimate of the portion of the forecast error variance of a specified variable attributable to a 1 standard deviation EBP shock under the EBP–σ (σ–EBP) identification scheme; the shaded bands denote the 90-percent pointwise credible sets corresponding to the EBP–σ identification scheme.

uncertainty shocks. Moreover, financial disruptions have an appreciably larger effect on the broad stock market compared with the JLN uncertainty shocks—the EBP shocks are estimated to explain about 40 percent of the forecast error variance in stock prices, on balance.

In combination, the above results are consistent with theoretical mechanisms that emphasize the presence of frictions in financial markets—and their effect on the effective supply on credit—as an important conduit through which fluctuations in uncertainty are propagated to the real economy (Arellano et al., 2012; Christiano et al., 2014; Gilchrist et al., 2014). In response to an unanticipated increase in uncertainty, distortions in financial markets induce a tightening of financial conditions—effectively reducing the supply of credit available to businesses and households—which leads to a decline in spending and production and a drop in the stock market. In addition, if we restrict our attention to uncertainty proxies that are not based solely on stock market data, our results also support the view that financial and uncertainty shocks are both important drivers of business cycles.

FIGURE 10: Historical Variance Decomposition of Selected Variables
(σ–EBP Identification)
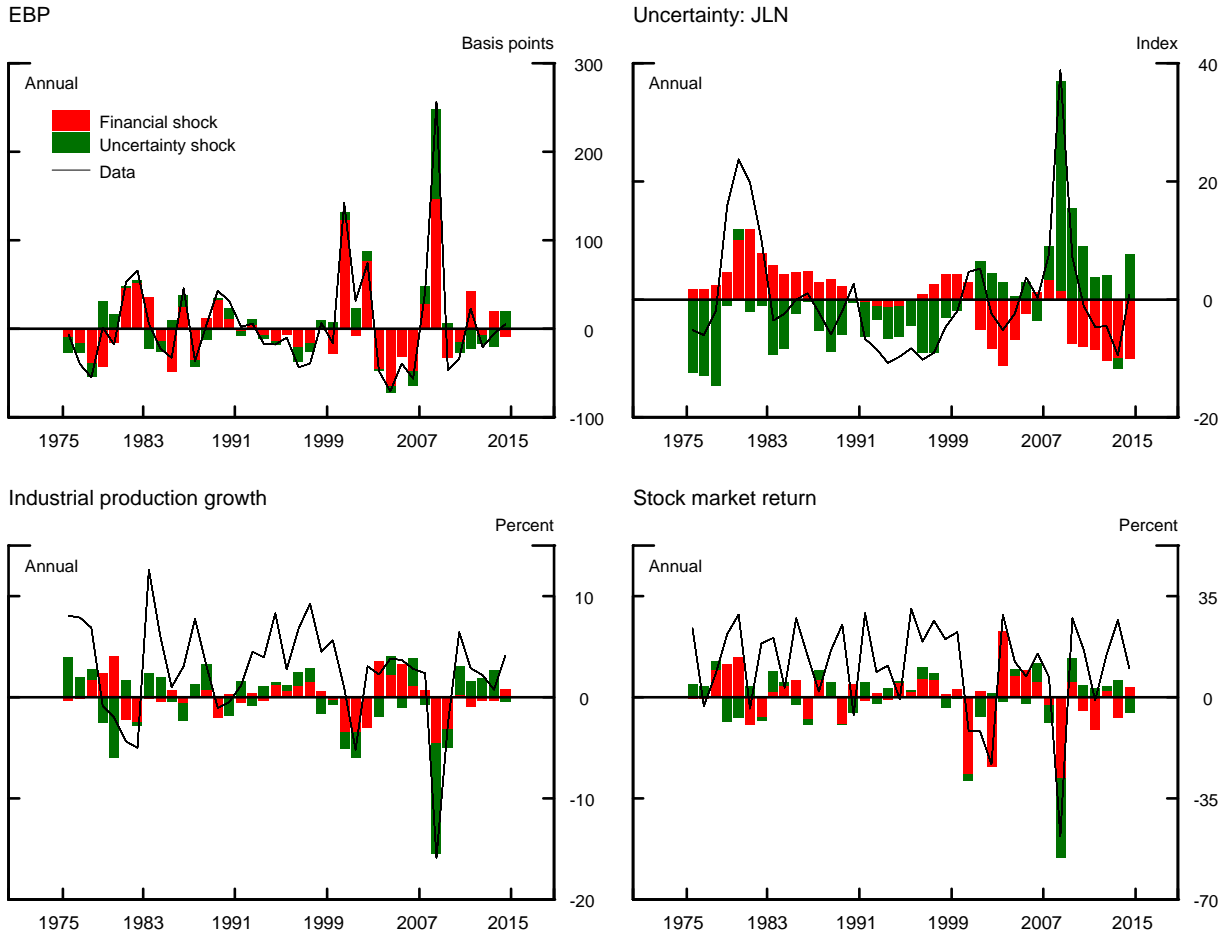
NOTE: Sample period: annual data from 1976 to 2014. The shaded regions in each panel depict the historical contributions of shocks to the EBP (red) and the JLN uncertainty measure (green) to the specified variable; the two shocks are orthogonalized using the σ–EBP identification scheme. The actual series (solid lines) are expressed in deviations from their respective estimated means.

4.1 Historical Significance of Financial and Uncertainty Shocks

To put the above results into a historical perspective, this section examines the role of financial and uncertainty shocks in economic fluctuations over the past 40 years. That is, for the JLN uncertainty proxy, the EBP, industrial production, and stock prices, we calculate the portion of the actual series that is attributable to these two types of shocks over the 1976–2014 period.[17] To better delineate the relative contributions of these two shocks to economic fluctuations, we present the data at an annual frequency.[18]

---

[17]We compute the historical variance decomposition at the OLS estimates of the reduced-form parameters. The sample used for the estimation includes actual data and the dummy observations used to implement the Minnesota prior (see Appendix B for details on the prior specification).

[18]The EBP and the JLN uncertainty proxy are measured as of December of each year, while the growth of industrial production and the stock market return are expressed in year-over-year changes.

The results of this exercise for the σ–EBP identification scheme are shown in Figure 10. According to the historical decomposition implied by this identification scheme, our identified financial shocks account for the majority of the movements in the EBP—outside the Great Recession, the corresponding uncertainty shocks do not appear to have had much of an effect on financial market conditions. In contrast, the EBP shocks account roughly for about as much of the variability in the JLN measure of uncertainty as do the uncertainty shocks.

Shocks emanating from the financial sector also shaped importantly the ups and downs in economic activity over our sample period. However, the economic significance of credit supply shocks has varied considerably over the past four decades. Such shocks played a distinctly secondary role in economic fluctuations during the first half of our sample, a result consistent with the heavy regulation of financial institutions and markets during this period. In addition, there is considerable empirical evidence showing that the economic downturns of the 1970s were influenced significantly by the OPEC-induced increases in oil prices (Hamilton, 1983), while the recessions of the early 1980s owed importantly to the tightening of monetary policy under the then-Fed Chairman Volcker, who was determined to fight inflation and reverse the rise in inflation expectations (Lindsey et al., 2005).

Financial shocks assumed new importance in the wake of financial deregulation and the associated financial deepening that took place during the second half of the 1980s and the early 1990s. According to our estimates, a pronounced tightening in financial market conditions occurred in periods surrounding the 2001 and 2007–09 cyclical downturns, and adverse credit supply shocks account for significant portions of the decline in real industrial output and equity valuations during these two recessions. On the other hand, easy financial conditions—at least in retrospect—characterized much of the mid-1990s and mid-2000s, and economic activity and the stock market were buoyed substantially by expansionary credit supply shocks.

The Great Recession and its immediate aftermath is the one period in our sample during which economic uncertainty had an out-sized effect on macroeconomic outcomes. Adverse uncertainty shocks during this period contributed significantly to a tightening of financial conditions, a drop in industrial production, and the collapse in stock prices. In fact, it may be that the combination of these two types of shocks has an especially pernicious effect on the macroeconomy, which explains the prolonged slump.

A qualitatively similar historical narrative emerges under the EBP–σ identification scheme. As shown in Figure 11, changes in credit market conditions over the past four decades are again driven primarily by financial shocks, although adverse uncertainty shocks contributed noticeably to the massive tightening of financial conditions experienced at the nadir of the 2008–09 crisis. Under this identification scheme, financial shocks continue to shape importantly the cyclical swings in economic uncertainty, especially during the latter part of our sample. And while these identifying assumptions assign a somewhat greater role in economic fluctuations to disruptions in the credit intermediation process, uncertainty shocks remain a significant source of macroeconomic instability, especially during the Great Recession.

26

FIGURE 11: Historical Variance Decomposition of Selected Variables
(EBP–σ Identification)
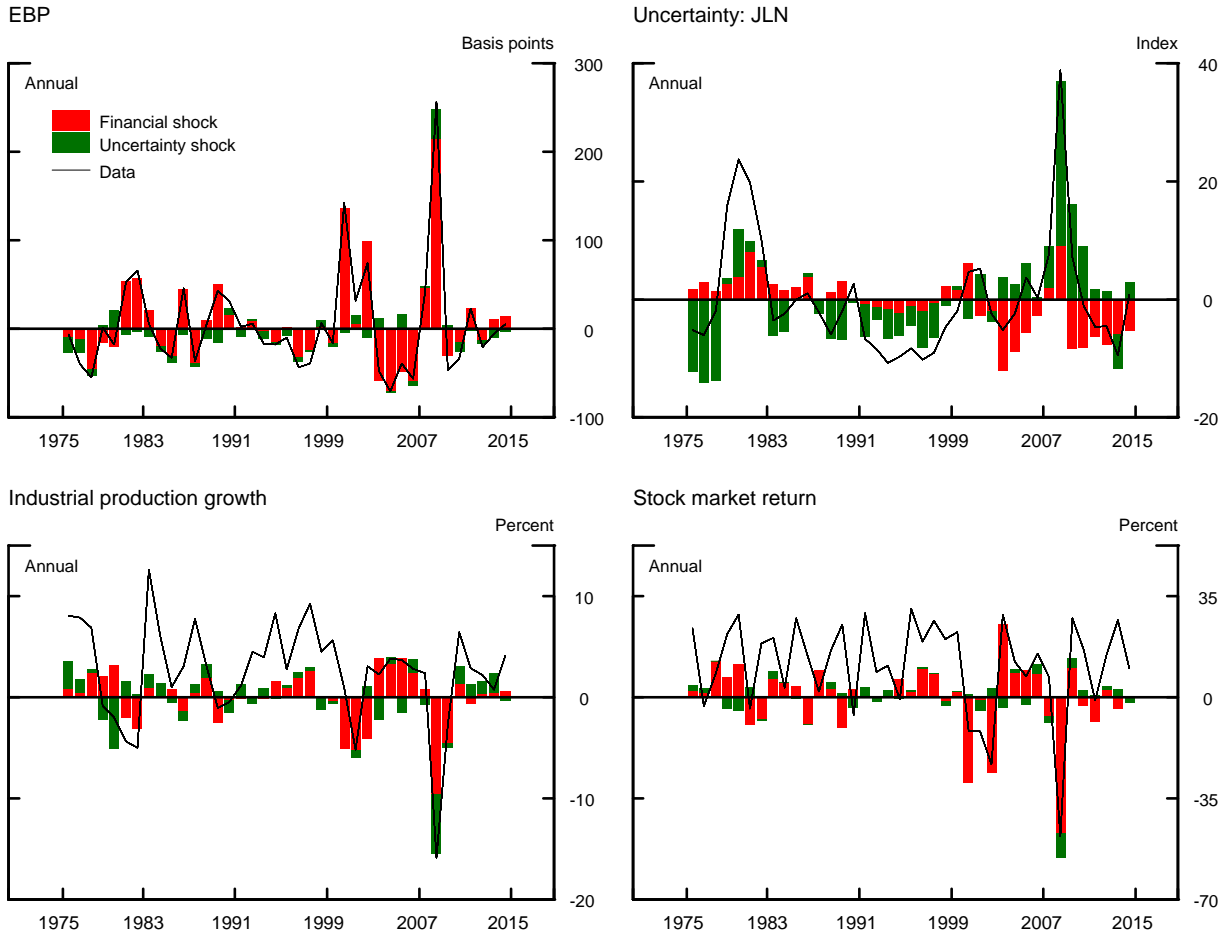
NOTE: Sample period: annual data from 1976 to 2014. The shaded regions in each panel depict the historical contributions of shocks to the EBP (red) and the JLN uncertainty measure (green) to the specified variable; the two shocks are orthogonalized using the EBP–σ identification scheme. The actual series (solid lines) are expressed in deviations from their respective estimated means.

## 4.2 The Role of the Great Recession

The Great Recession is arguably the defining moment of U.S. post-war economic history and one in which financial and uncertainty shocks appeared to have played an especially prominent role, according to our results. Hence, it is natural to ask to what extent are the above results influenced by the events surrounding this extraordinary period of economic and financial turmoil. To answer this question, we re-estimate our SVAR on the 1973:M1–2007:M12 subsample. Figure 12 summarizes the results of this exercise for the σ–EBP identification scheme, while Figure 13 does the same for the EBP–σ identification scheme. For comparison purposes, the solid lines and the shaded bands in both figures show the results based on the full (1973:M1–2015:M3) sample period.

As shown by the dashed lines in panel (a) of Figure 12, the macroeconomic impact of the JLN

FIGURE 12: Economic Effects of Uncertainty and Financial Shocks
(Subsample Analysis under the σ–EBP Identification)
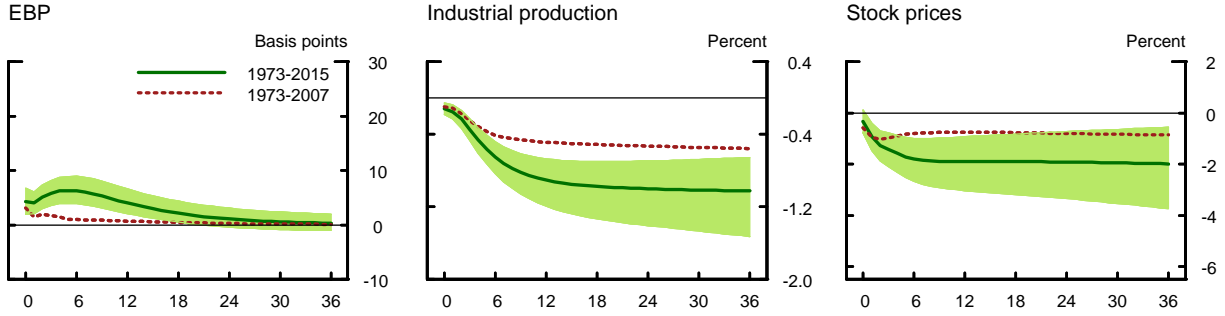
(a) Responses of selected variables to a JLN uncertainty shock
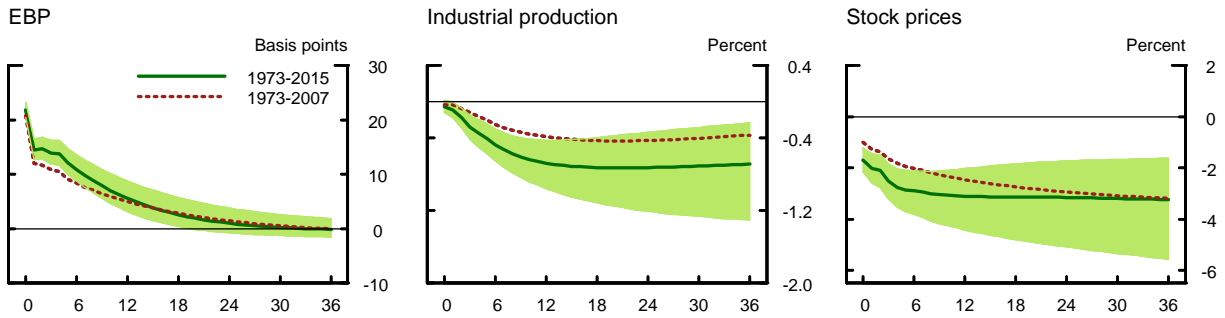
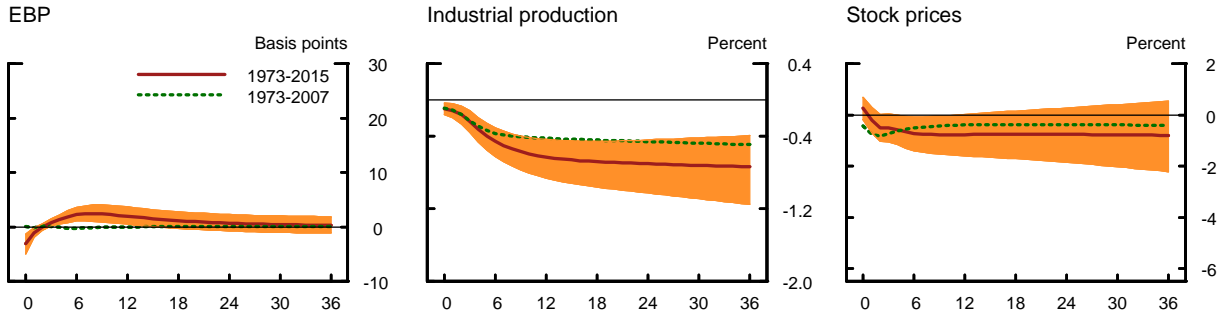(b) Responses to selected variables to an EBP shock

NOTE: The solid and dotted lines in panel (a) depict median responses of selected variables to the JLN uncertainty shock of 1 standard deviation (based on the 1973:M1–2015:M3 sample period), while those in panel (b) depict median responses of the same variables to the EBP shock of 1 standard deviation (again based on the 1973:M1–2015:M3 sample period); both shocks are orthogonalized using the σ–EBP identification scheme. Responses are based on the same VAR specification estimated over two sample periods: solid = 1973:M1–2015:M3; and dotted = 1973:M1–2007:M12. The shaded bands represent the 90-percent pointwise credible sets based on the 1973:M1–2015:M3 sample period.

uncertainty shocks is influenced notably by the Great Recession. Excluding the post-2007 data from our sample implies a more modest effect of uncertainty shocks on both the industrial production and the stock market. This difference appears to reflect the fact that during this period, the JLN uncertainty shocks do not elicit an economically meaningful tightening of financial conditions under the σ–EBP identification.

According to panel (b) of Figure 12, the macroeconomic impact of financial shocks is also influenced by the Great Recession, primarily reflecting the fact that the response of the EBP to its own shock is somewhat less persistent over the 1973–2007 period. The reduction in persistence implies a less severe decline in industrial production in response to a financial shock, especially over the first 12 months or so. The economic effect of financial shocks on stock prices is also somewhat attenuated in the immediate aftermath of such a shock.

Figure 13 shows the same set of the IRFs under the EBP–σ identification scheme. As shown in

FIGURE 13: Economic Effects of Uncertainty and Financial Shocks
(Subsample Analysis under the EBP–σ Identification)

(a) Responses of selected variables to a JLN uncertainty shock

(b) Responses of selected variables to an EBP shock

NOTE: The solid and dotted lines in panel (a) depict median responses of selected variables to the JLN uncertainty shock of 1 standard deviation (based on the 1973:M1–2015:M3 sample period), while those in panel (b) depict median responses of the same variables to the EBP shock of 1 standard deviation (again based on the 1973:M1–2015:M3 sample period); both shocks are orthogonalized using the EBP–σ identification scheme. Responses are based on the same VAR specification estimated over two sample periods: solid = 1973:M1–2015:M3; and dotted = 1973:M1–2007:M12. The shaded bands represent the 90-percent pointwise credible sets based on the 1973:M1–2015:M3 sample period.

panels (a) and (b), when we estimate the VAR using only the data over the 1973–2007 period, the macroeconomic impact of uncertainty and financial shocks on both the real industrial output and the stock market—though economically and statistically still significant—is not as pronounced as that implied by the full sample period. As was the case under the σ–EBP identification scheme, uncertainty shocks under the EBP–σ identification also fail to elicit an economically significant tightening of financial conditions during the 1973–2007 period (panel (a)). By the same token, financial shocks induce, on balance, a less severe and protracted tightening of financial conditions, which accounts for their more limited macroeconomic effects (panel (b)).

4.3 Validation of Financial and Uncertainty Shocks

The historical variance decomposition presented above clearly indicates that the identified financial and uncertainty shocks were important drivers of fluctuations in economic activity and swings in broad equity prices over the past four decades. At the same time however, a natural question that emerges from this analysis is whether these two types of shocks in fact represent distinct sources of cyclical fluctuations or whether they are simply emblematic of traditional origins of macroeconomic instability.

To examine this hypothesis more formally, we look at the correlations between the identified financial and uncertainty shocks and other widely cited economic disturbances, all of which are external to our VAR system. At monthly frequency, we consider two types of popular shocks: monetary policy and oil price shocks. To measure unanticipated changes in the stance of monetary policy, we rely on high-frequency financial market data. Our first monetary policy shock corresponds to the "target surprise" proposed by Kuttner (2001), which measures the unexpected change in the target federal funds rate associated with an FOMC announcement.[19] In addition, we use changes in the (on-the-run) 2-year Treasury yield over a narrow window bracketing FOMC announcements as monetary policy surprises, which provide a more complete characterization of the unanticipated changes in the stance of policy, according to Gilchrist et al. (2015).[20]

We also consider two monthly measures of oil price shocks. The first set of oil shocks corresponds to residuals from an AR(1) model of the log-difference of the real price of the WTI crude. The second measure of oil supply shocks is from Killian (2009), who employs a SVAR-based approach to identify the underlying demand and supply shocks in the global crude oil market.

At quarterly frequency, we concern ourselves with technology and fiscal shocks. The first set of technology shocks corresponds to shocks to labor productivity identified by Mertens and Ravn (2011a) using a SVAR-based approach, which are orthogonal to tax shocks derived from the narrative approach of Romer and Romer (2010). As an alternative proxy, we also use residuals from an AR(1) model of the log-difference in the utilization-adjusted total factor productivity (TFP), which attempts to adjust measured TFP for a range of non-technological factors that can drive a wedge between TFP and technology (Basu et al., 2006).

On the fiscal front, we consider the surprise tax policy changes from Mertens and Ravn (2011b), which are based on the narrative approach of Romer and Romer (2010); the anticipated tax policy changes of Leeper et al. (2013); and the unanticipated changes in the expected present value of government spending in response to military events from Owyang et al. (2013). All told, our list

---

[19]Specifically, the unanticipated change in the funds rate is calculated as the change—with minor adjustments—in the current-month federal funds futures contract rate in a 30-minute window (10 minutes before to 20 minutes after) around the FOMC announcement; see Kuttner (2001) for details.

[20]As emphasized by Gürkaynak et al. (2005), using solely the target surprises to characterize the unanticipated changes in the stance of monetary policy is incomplete because such an approach omits the effect of changes in the future policy rates that are independent of the shock to the current target rate and which are closely associated with the FOMC statements that accompany changes in the target rate. As shown by Gilchrist et al. (2015), however, the first-order effects of monetary policy actions can be summarized adequately by the intraday changes in the 2-year nominal Treasury yield bracketing FOMC announcements.

TABLE 4: Correlations Between Uncertainty, Financial, and Other External Shocks

| | Identification Scheme | | | |
| | σ–EBP | | EBP–σ | |
	Uncertainty	Financial	Uncertainty	Financial
(a) *Monthly External Shocks*				
FFR target surprises[a]	0.03	0.03	0.02	0.04
2-year Treasury yield surprises[b]	0.08	0.08	0.05	0.09
Real price of oil shocks[c]	−0.07	0.05	0.07	−0.05
Oil supply shocks[d]	0.05	0.02	−0.00	0.06
(b) *Quarterly External Shocks*				
Technology shocks[e]	−0.08	−0.08	−0.05	−0.11
TFP growth shocks[f]	−0.16**	0.09	0.13	−0.12
Unanticipated tax shocks[g]	−0.03	−0.04	−0.03	−0.07
Anticipated tax shocks[h]	−0.06	−0.08	0.05	−0.08
Defense spending shocks[i]	−0.05	0.08	−0.10	−0.02

NOTE: The entries in the table denote the pairwise correlations between the specified external shock and the financial (EBP) and uncertainty (JLN) shocks identified under the σ–EBP and EBP–σ identification schemes. Sample period for monthly financial and uncertainty shocks is 1975:M1 to 2015:M3; the respective quarterly shock series are the quarterly averages of the corresponding monthly values. * $p < .10$; ** $p < .05$; and *** $p < .01$.

[a] Unanticipated changes in the target federal funds rate in the 30-minute window bracketing FOMC announcements; see Kuttner (2001) (1992:M2–2015:M3, $T = 278$).

[b] Changes in the (on-the-run) 2-year Treasury yield in the 30-minute window bracketing FOMC announcements; see Gilchrist et al. (2015) (1994:M2–2015:M3, $T = 254$).

[c] Residuals from a first-order autoregressive model of the log-difference in the real price of the WTI crude (1975:M1–2015:M3, $T = 483$).

[d] Crude oil supply shock from Killian (2009) (1975:M1–2007:M12 $T = 396$).

[e] Technology shocks from Mertens and Ravn (2011a) (1975:Q1–2006:Q4, $T = 128$).

[f] Residuals from a first-order autoregressive model of the log-difference in the utilization-adjusted total factor productivity; see Basu et al. (2006) (1975:Q1–2015:Q1, $T = 161$).

[g] Unanticipated tax shocks from Mertens and Ravn (2011b) (1975:Q1–2006:Q4, $T = 128$).

[h] Anticipated tax changes from Leeper et al. (2013) (1975:Q1–2006:Q4, $T = 128$).

[i] Defense spending shocks from Owyang et al. (2013) (1975:Q1–2013:Q4, $T = 156$).

of external shocks spans the space of disturbances commonly considered to be the most important drivers of aggregate fluctuations.

The pairwise correlations between these external shocks and our identified financial and uncertainty shocks are reported in Table 4. As evidenced by the entries in the table, there appears to be no systematic contemporaneous association between financial and uncertainty shocks and other typical macroeconomic disturbances under either identification scheme. Virtually all pairwise correlations are statistically indistinguishable from zero and all of them are very small in economic terms. These results provide strong corroborative evidence for the hypothesis that the identified financial and uncertainty shocks represent distinct sources of economic disturbances, independent of traditional business cycle shocks.

5 Conclusion

This paper employs the penalty function approach to jointly identify shocks to financial conditions and economic uncertainty and to trace out the impact of these two types of disturbances on the economy. The two structural innovations are identified using the criterion that each shock should maximize the impulse response of its respective target variable over a pre-specified horizon, an approach that allows us to orthogonalize shocks that have otherwise very similar qualitative effects on the economy. Intuitively, we assume that a persistent tightening of financial conditions is due to an adverse financial shock, whereas prolonged periods of elevated economic uncertainty are driven by uncertainty shocks. Our identification strategy also does not rule out a contemporaneous response of financial conditions to uncertainty shocks or vice versa.

We implement this approach in the context of a standard monetary VAR, augmented with the excess bond premium—an indicator of the tightness of financial conditions—and various proxies for economic uncertainty. Our results indicate that financial shocks have a significant adverse effect on economic outcomes and that such shocks were an important source of cyclical fluctuations since the mid-1980. In addition, uncertainty shocks, especially those implied by uncertainty proxies based on real economic data, are also an important source of macroeconomic disturbances; such uncertainty shocks appear to have a significant more pronounced economic impact in situations where they elicit a concomitant tightening of financial conditions.

All told, the evidence presented in this paper provides a considerable support for the hypothesis that financial and uncertainty shocks have both played a significant role in business cycle fluctuations over the past four decades. This finding is buttressed importantly by the evidence that our identified financial and uncertainty shocks are uncorrelated with external instruments that serve as proxies for a range of traditional cyclical disturbances. In fact, according to our results, the combination of financial and uncertainty shocks fully accounts for the severe contraction in real industrial output and the collapse of the stock market during the Great Recession.

References

ADRIAN, T. AND H. S. SHIN (2010): "Liquidity and Leverage," *Journal of Financial Intermediation*, 19, 418–437.

ARELLANO, C., Y. BAI, AND P. J. KEHOE (2012): "Financial Markets and Fluctuations in Volatility," Staff Report No. 466, Federal Reserve Bank of Minneapolis.

ARIAS, J., J. RUBIO-RAMIREZ, AND D. WAGGONER (2013): "Inference Based on SVARs Identified with Sign and Zero Restrictions," Working Paper, Dept. of Economics, Duke University.

BACHMANN, R., S. ELSTNER, AND E. SIMS (2013): "Uncertainty and Economic Activity: Evidence From Business Survey Data," *American Economic Journal: Macroeconomics*, 5, 217–249.

BAKER, S. R., N. BLOOM, AND S. J. DAVIS (2015): "Measuring Economic Policy Uncertainty," NBER Working Paper No. 21633.

BARSKY, R. B. AND E. R. SIMS (2011): "News Shocks and Business Cycles," *Journal of Monetary Economics*, 58, 273–289.

BARTELS, R. (1982): "The Rank Version of von Neumann's Ratio Test for Randomness," *Journal of the American Statistical Association*, 77, 40–46.

BASU, S., J. G. FERNALD, AND M. S. KIMBALL (2006): "Are Technology Improvements Contractionary?" *American Economic Review*, 96, 1418–1448.

BEKAERT, G., M. HOEROVA, AND M. LO DUCA (2013): "Risk, Uncertainty, and Monetary Policy," *Journal of Monetary Economics*, 60, 771–788.

BLOOM, N. (2009): "The Impact of Uncertainty Shocks," *Econometrica*, 77, 623–685.

——— (2014): "Fluctuations in Uncertainty," *Journal of Economic Perspectives*, 28, 153–176.

BLOOM, N., M. FLOETOTTO, N. JAIMOVICH, I. SAPORTA-EKSTEN, AND S. TERRY (2012): "Really Uncertain Business Cycles," NBER Working Paper No. 18245.

BOIVIN, J., M. GIANNONI, AND D. STEVANOVIĆ (2013): "Dynamic Effects of Credit Shocks in a Data-Rich Environment," Staff Report No. 2013, Federal Reserve Bank of New York.

BRUNNERMEIER, M. K. AND Y. SANNIKOV (2014): "A Macroeconomic Model with a Financial Sector," *American Economic Review*, 104, 379–421.

CALDARA, D. AND C. KAMPS (2012): "The Analytics of SVARs: A Unified Framework to Measure Fiscal Multipliers," Finance and Economics Discussion Series Paper No. 2012-20, Federal Reserve Board.

CAMPBELL, J. Y., M. LETTAU, B. G. MALKIEL, AND Y. XU (2001): "Have Individual Stocks Become More Volatile? An Empirical Exploration of Idiosyncratic Risk," *Journal of Finance*, 56, 1–44.

CARHART, M. M. (1997): "On Persistence in Mutual Fund Performance," *Journal of Finance*, 52, 57–82.

CHRISTIANO, L. J., R. MOTTO, AND M. ROSTAGNO (2014): "Risk Shocks," *American Economic Review*, 104, 27–65.

D'AMICO, S. AND A. ORPHANIDES (2008): "Uncertainty and Disagreement in Economic Forecasting," Finance and Economics Discussion Series Paper No. 2008-56, Federal Reserve Board.

DEL NEGRO, M. AND F. SCHORFHEIDE (2011): "Bayesian Macroeconometrics," in *Handbook of Bayesian Econometrics*, ed. by J. Geweke, G. Koop, and H. van Dijk, Oxford University Press, Chapter 7.

ELLIOTT, G. AND U. K. MÜLLER (2006): "Efficient Tests for General Persistent Time Variation in Regression Coefficients," *Review of Economic Studies*, 73, 907–940.

FAJGELBAUM, P., E. SCHAAL, AND M. TASCHEREAU-DUMOUCHEL (2014): "Uncertainty Traps," NBER Working Paper No. 19973.

FAMA, E. F. AND K. R. FRENCH (1992): "The Cross-Section of Expected Stock Returns," *Journal of Finance*, 47, 427–465.

FAUST, J. (1998): "The Robustness of Identified VAR Conclusions About Money," *Carnegie-Rochester Conference Series on Public Policy*, 49, 207–244.

FAUST, J., S. GILCHRIST, J. H. WRIGHT, AND E. ZAKRAJŠEK (2013): "Credit Spreads as Predictors of Real-Time Economic Activity: A Bayesian Model-Averaging Approach," *Review of Economics and Statistics*, 95, 1501–1519.

GILCHRIST, S., D. LÓPEZ-SALIDO, AND E. ZAKRAJŠEK (2015): "Monetary Policy and Real Borrowing Costs at the Zero Lower Bound," *American Economic Journal: Macroeconomics*, 7, 77–109.

GILCHRIST, S., J. W. SIM, AND E. ZAKRAJŠEK (2014): "Uncertainty, Financial Frictions, and Investment Dynamics," NBER Working Paper No. 20038.

GILCHRIST, S., V. YANKOV, AND E. ZAKRAJŠEK (2009): "Credit Market Shocks and Economic Fluctuations: Evidence From Corporate Bond and Stock Markets," *Journal of Monetary Economics*, 56, 471–493.

GILCHRIST, S. AND E. ZAKRAJŠEK (2012): "Credit Spreads and Business Cycle Fluctuations," *American Economic Review*, 102, 1692–1720.

GÜRKAYNAK, R. S., B. SACK, AND E. SWANSON (2005): "Do Actions Speak Louder Than Words? The Response of Asset Prices to Monetary Policy Actions and Statements," *International Journal of Central Banking*, 1, 55–93.

HAMILTON, J. D. (1983): "Oil and the Macroeconomy Since World War II," *Journal of Political Economy*, 91, 228–248.

HANSEN, N., S. D. MÜLLER, AND P. KOUMOUTSAKOS (2003): "Reducing the Time Complexity of the Derandomized Evolution Strategy With Covariance Matrix Adaption (CMA-ES)," *Evolutionary Computation*, 11, 1–18.

JURADO, K., S. C. LUDVIGSON, AND S. NG (2015): "Measuring Uncertainty," *American Economic Review*, 105, 1177–1216.

KILLIAN, L. (2009): "Not All Oil Price Shocks are Alike: Disentangling Demand and Supply Shocks in the Crude Oil Market," *American Economic Review*, 99, 1053–1069.

KURMANN, A. AND C. OTROK (2013): "News Shocks and the Slope of the Term Structure of Interest Rates," *American Economic Review*, 103, 2612–2632.

KUTTNER, K. N. (2001): "Monetary Policy Surprises and Interest Rates: Evidence From the Fed Funds Futures Market," *Journal of Monetary Economics*, 47, 523–544.

LEEPER, E. M., T. B. WALKER, AND S. S. YANG (2013): "Fiscal Foresight and Information Flows," *Econometrica*, 81, 1115–1145.

LINDSEY, D. E., A. ORPHANIDES, AND R. H. RASCHE (2005): "The Reform of October 1979: How It Happened and Why," *Review, Federal Reserve Bank of St. Louis*, 87, 187–235.

LÓPEZ-SALIDO, D., J. C. STEIN, AND E. ZAKRAJŠEK (2016): "Credit-Market Sentiment and the Business Cycle," NBER Working Paper No. 21879.

LUDVIGSON, S. C., S. MA, AND S. NG (2016): "Uncertainty and Business Cycles: Exogenous Impulse or Endogenous Response?" Working Paper, Dept. of Economics, New York University.

MERTENS, K. AND M. O. RAVN (2011a): "Technology-Hours Redux: Tax Changes and the Measurement of Technology Shocks," in *NBER International Seminar on Macroeconomics*, Chicago: The University of Chicago Press, vol. 7, 41–76.

——— (2011b): "Understanding the Aggregate Effects on Anticipated and Unanticipated Tax Policy Shocks," *Review of Economic Dynamics*, 14, 27–54.

MOUNTFORD, A. AND H. UHLIG (2009): "What Are the Effects of Fiscal Policy Shocks?" *Journal of Applied Econometrics*, 24, 960–992.

NEWEY, W. K. AND K. D. WEST (1987): "A Simple, Positive Semi-Definite, Heteroskedasticity- and Autocorrelation-Consistent Covariance Matrix," *Econometrica*, 55, 703–708.

——— (1994): "Automatic Lag Selection in Covariance Matrix Estimation," *Review of Economic Studies*, 61, 631–653.

ORLIK, A. AND L. L. VELDKAMP (2014): "Understanding Uncertainty Shocks and the Role of Black Swans," NBER Working Paper No. 20445.

OWYANG, M. T., V. A. RAMEY, AND S. ZUBAIRY (2013): "Are Government Spending Multipliers Greater During Periods of Slack: Evidence from Twentieth-Century Historical Data," *American Economic Review*, 103, 129–134.

POPESCU, A. AND F. SMETS (2010): "Uncertainty, Risk-Taking, and the Business Cycle in Germany," *CESifo Economic Studies*, 56, 596–626.

ROMER, C. D. AND D. H. ROMER (2010): "The Macroeconomic Effects of Tax Changes: Estimates Based on a New Measure of Fiscal Shocks," *American Economic Review*, 100, 763–801.

ROUSSEEUW, P. J. AND C. CROUX (1993): "Alternatives to Median Absolute Deviation," *Journal of the American Statistical Association*, 88, 1273–1283.

STOCK, J. H. AND M. W. WATSON (2012): "Disentagling the Channels of the 2007–09 Recession," *Brookings Papers on Economic Activity*, 44, 81–135.

UHLIG, H. (2003): "What Moves Real GNP?" Working Paper, Humboldt University Berlin.

——— (2005): "What Are the Effects of Monetary Policy on Output? Results From an Agnostic Identification Procedure," *Journal of Monetary Economics*, 52, 381–419.

VAN NIEUWERBURGH, S. AND L. L. VELDKAMP (2006): "Learning Asymmetries in Real Business Cycles," *Journal of Monetary Economics*, 53, 753–772.

ZELLNER, A. (1971): *An Introduction to Bayesian Inference in Econometrics*, New York: John Wiley & Sons Inc.

Appendices – For Online Publication

A   Data Appendix

This appendix provides a brief description of the six uncertainty proxies used in the analysis.

RVOL measure of uncertainty.   The realized equity volatility is calculated as the (annualized) standard deviation of the daily value-weighted total market (log) return from the Center for Research in Security Prices (CRSP) database. To mitigate the effects of large daily swings in equity prices—many of which occurred during the 2007–08 financial crisis—we use the robust estimator of scale proposed by Rousseeuw and Croux (1993) to calculate the monthly standard deviation of daily stock returns.

IVOL measure of uncertainty.   This uncertainty proxy is a monthly version—with minor modifications—of the quarterly measure proposed by Gilchrist et al. (2014). First, we extracted daily stock returns for all U.S. nonfinancial corporations with at least 500 trading days of data. This selection criterion yielded a panel of 14,856 firms over the period from October 1, 1972 to March 31, 2015. To ensure that our results were not driven by a small number of extreme observations, we eliminated all firm/day observations with a daily absolute return in excess of 50 percent.

The estimate of uncertainty is based on the following three-step procedure. First, we remove the forecastable variation in daily excess returns using the standard (linear) factor model:

$$(R_{it_d} - r_{t_d}^f) = \alpha_i + \boldsymbol{\beta}_i' \mathbf{f}_{t_d} + u_{it_d}, \tag{A-1}$$

where i indexes firms and t_d, $d = 1, \ldots, D_t$, indexes trading days in month t. In equation (A-1), R_{it_d} denotes the (total) daily return of firm i, $r_{t_d}^f$ is the risk-free rate, and $\mathbf{f}_{t_d}$ is a vector of observable risk factors. In implementing the first step, we employ a 4-factor model—namely, the Fama and French (1992) 3-factor model, augmented with the momentum risk factor proposed by Carhart (1997).

In the second step, we use the robust scale estimator of Rousseeuw and Croux (1993) to calculate the monthly firm-specific standard deviation of the daily idiosyncratic returns—that is, the OLS residuals $\hat{u}_{it_d}$ from equation (A-1). Denoted by σ_{it}, this provides us with an estimate of time-varying equity volatility for firm i, a measure that is purged of the forecastable variation in expected returns.

In the third step, we assume that the firm-specific measure of uncertainty σ_{it} follows an autoregressive process of the form:

$$\log \sigma_{it} = \gamma_i + \delta_i t + \sum_{k=1}^{3} \rho_k \log \sigma_{i,t-k} + v_t + \epsilon_{it},$$

where γ_i denotes a firm fixed effect intended to control for the cross-sectional heterogeneity in σ_{it}, while the firm-specific term $\delta_i t$ captures secular trends in the idiosyncratic risk of publicly traded U.S. nonfinancial firms documented by Campbell et al. (2001).

The IVOL uncertainty proxy corresponds to the sequence of estimated time fixed effects $\hat{v}_t$, $t = 1, \ldots, T$, which captures shocks to idiosyncratic volatility that are common to all firms. As emphasized by Gilchrist et al. (2014), the presence of the common variation in the volatility of idiosyncratic equity returns is essential because if fluctuations in idiosyncratic volatility were themselves entirely idiosyncratic, the macroeconomic impact of such uncertainty shocks should wash out in the aggregate.

VXO measure of uncertainty. The VXO uncertainty proxy corresponds to the option-implied volatility calculated from a hypothetical at the money S&P 100 option 30 days to expiration.

JLN measure of uncertainty. To measure economic uncertainty, Jurado et al. (2015) fit a factor model to a large cross section of macroeconomic and financial time series and use the estimated model to generate forecasts of all the series. Next, they assume that forecast errors of each individual series follow a univariate stochastic volatility process, and the cross-sectional average of these processes for a subset of variables pertaining to real economic activity becomes an estimate of macroeconomic uncertainty.

BBD measure of uncertainty. This index of economic policy uncertainty (EPU) is based on the frequency of newspaper references to policy-related economic uncertainty; see Baker et al. (2015) for details.

BES measure of uncertainty. To measure economic uncertainty, Bachmann et al. (2013) construct a measure of forecast dispersion using the Philadelphia Fed's Business Outlook Survey. This monthly survey of manufacturing firms contains qualitative information on the current state of firms' business conditions and their expectations of future business conditions. Bachmann et al. (2013) focus on two questions:

1. *General Business Conditions*: What is your evaluation of the level of general business activity six months from now versus [current month]? *Answers*: decrease; no change; increase.

2. *Company Business Indicators*: Shipments six months from now versus [current month]? *Answers*: decrease; no change; increase.

The qualitative survey responses to both questions are coded into three discrete numerical categories: $-1 =$ decrease; $0 =$ no change; and $1 =$ increase.
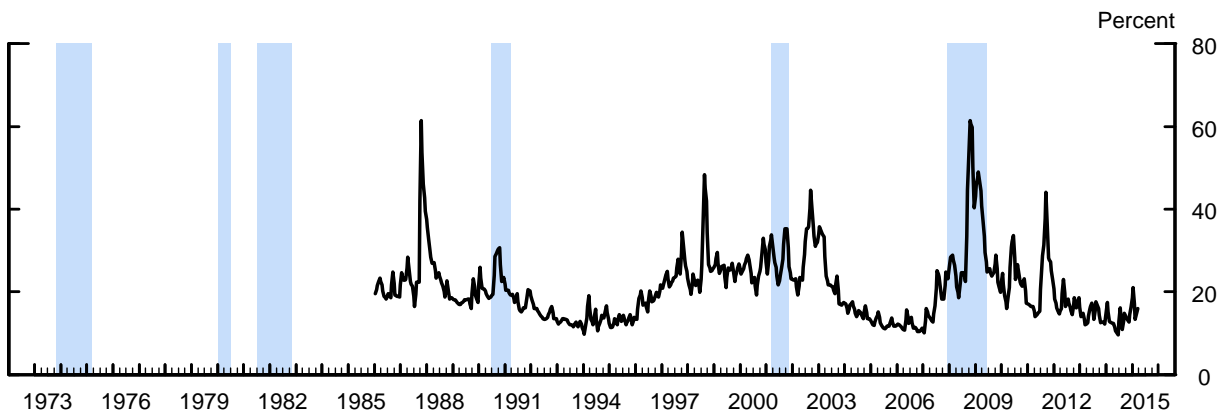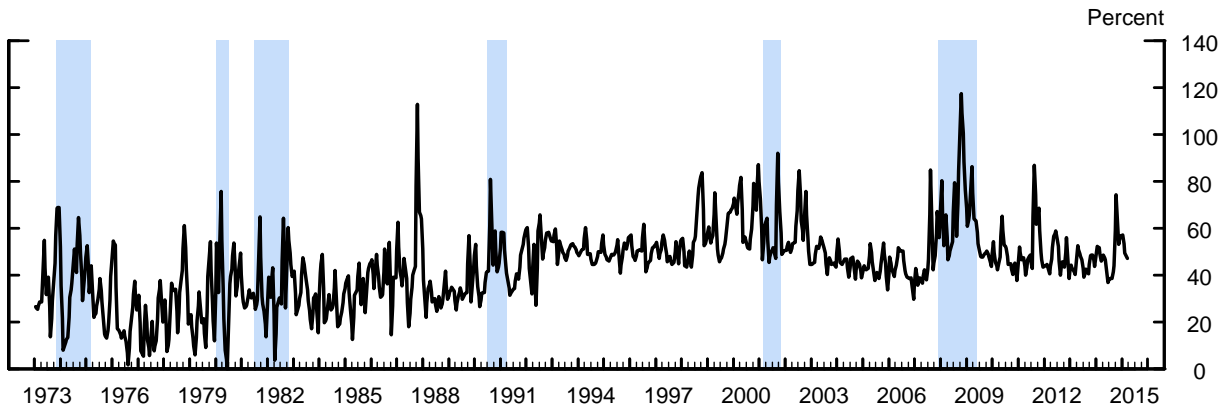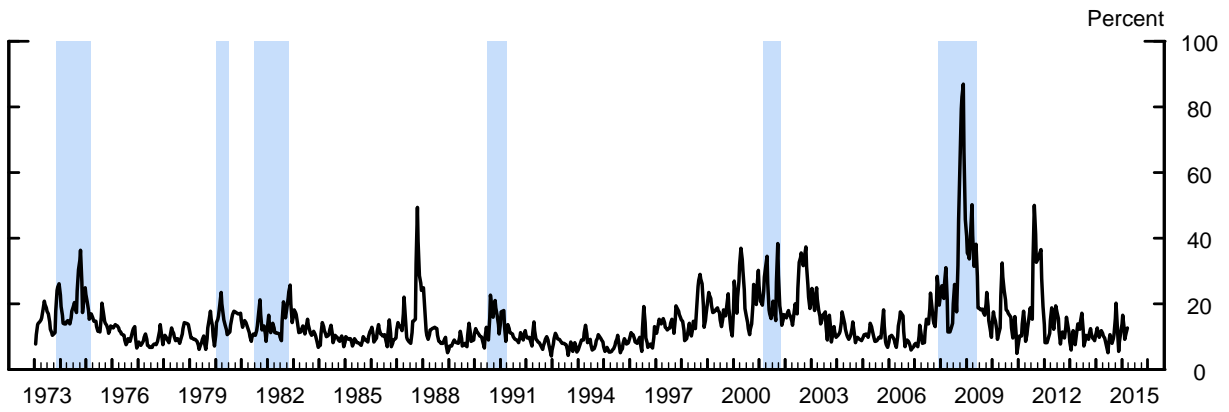
For each question, Bachmann et al. (2013) define Frac_t^+ as the (unweighted) proportion of firms that responded with "increase" at time t and Frac_t^- as the (unweighted) proportion of firms that responded with "decrease" at time t. The cross-sectional forecast dispersion for any of the two questions is then computed according to

$$D_t = \sqrt{\mathrm{Frac}_t^+ + \mathrm{Frac}_t^- - \left(\mathrm{Frac}_t^+ - \mathrm{Frac}_t^-\right)^2}.$$

The measure of time-varying business-level uncertainty used in this paper corresponds to the cross-sectional forecast dispersion for the question pertaining to general business conditions.

Figure A-1 shows the the time paths of the three uncertainty proxies that rely entirely on financial market data (RVOL, IVOL, and VXO), while Figure A-2 shows the time-series evolution of uncertainty measures not based exclusively on financial market data (JLN, BBD, and BES).
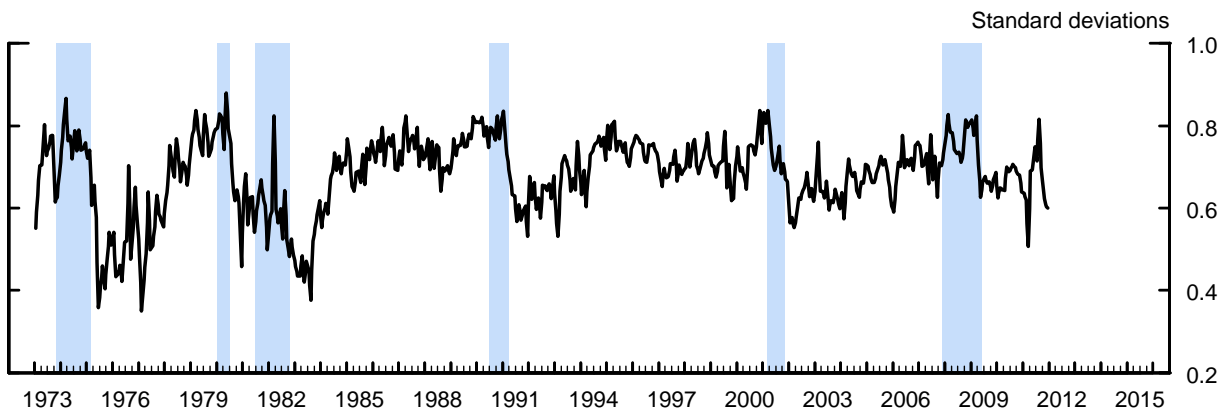
(a) Realized stock market volatility (RVOL)

(b) Idiosyncratic stock market volatility (IVOL)

(c) Option-implied volatility on the S&P 100 stock futures index (VXO)

NOTE: The panels of the figure show the three different measures of economic uncertainty based on exclusively on stock market data. The shaded vertical bars denote the NBER-dated recessions.

FIGURE A-2: Economic Uncertainty
(Proxies Not Based Exclusively on Stock Market Data)
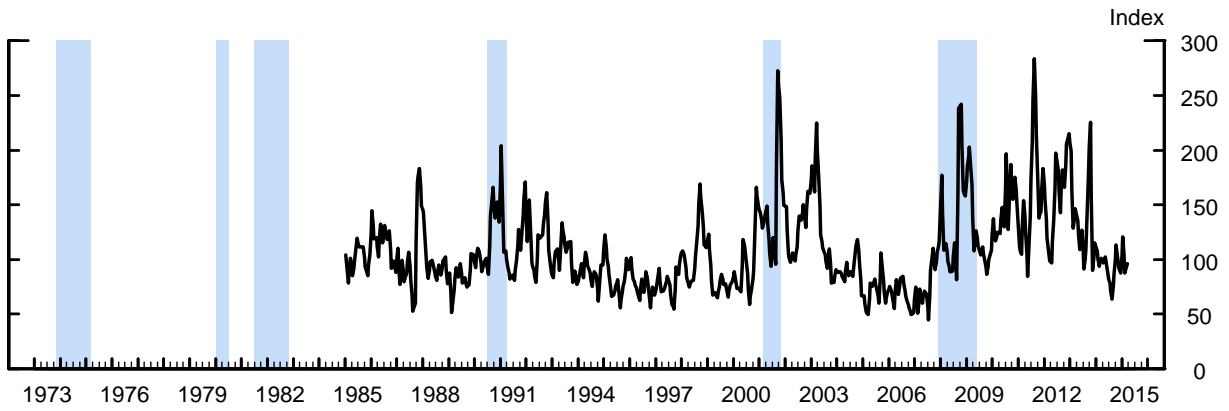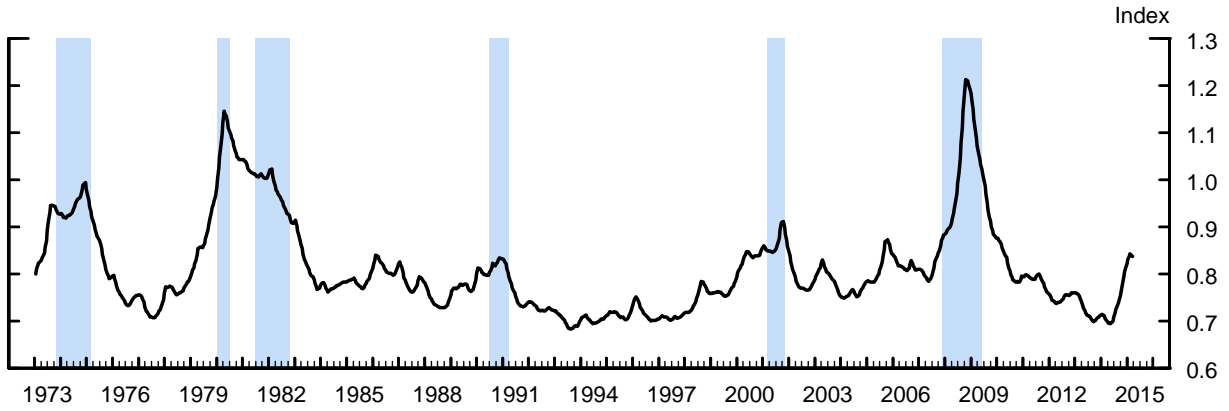
(a) Uncertainty index implied by forecast errors (JLN)

(b) Economic policy uncertainty index (BBD)

(c) Uncertainty based on forecast dispersion (BES)

NOTE: The panels of the figure show the three different measures of economic uncertainty that are not based on exclusively on stock market data. The shaded vertical bars denote the NBER-dated recessions.

TABLE A-1: Selected Characteristics of Different Economic Uncertainty Proxies

Uncertainty Proxy	Summary Statistic					
	CV	α_1	α_2	α_3	q_{LL}	RVN
RVOL[a]	0.61	0.70	0.13	0.03	-11.48	4.18***
IVOL[b]	0.38	0.63	0.18	0.05	-16.00	0.08
VXO[c]	0.40	0.83	0.02	0.06	-12.59	2.58**
JLN[d]	0.12	0.99	-0.75	0.17	-11.83	0.19
BBD[e]	0.36	0.71	0.04	0.06	-8.98	1.24
BES[f]	0.14	0.80	0.26	0.05	-13.69	-0.12

Uncertainty Proxy	Pairwise Correlations					
	RVOL	IVOL	VXO	JLN	BBD	BES
RVOL	1.00	0.62***	0.82***	0.47***	0.50***	0.13***
IVOL		1.00	0.57***	0.07	0.39***	0.23***
VXO			1.00	0.55***	0.49***	0.19***
JLN				1.00	0.31***	0.08*
BBD					1.00	0.02
BES						1.00

NOTE: The entries in the table denote the specified summary statistic: CV = coefficient of variation; α_k = partial autocorrelation at lag k; q_{LL} = the Elliott and Müller (2006) test statistic of the null hypothesis that the autoregressive coefficients from an AR(3) model are constant over time; and RVN = the Bartels (1982) test statistic of the null hypothesis that the OLS residuals from an AR(3) model are distributed randomly. * $p < .10$, ** $p < .05$, and *** $p < .01$.
[a] Realized equity volatility (1973:M1–2015:M3, $T = 507$).
[b] Idiosyncratic equity volatility based on Gilchrist et al. (2014) (1973:M1–2015:M3, $T = 507$).
[c] Option-implied volatility on the S&P 100 stock futures index (1986:M1–2015:M3, $T = 351$).
[d] Uncertainty measure based on Jurado et al. (2015) (1973:M1–2015:M3, $T = 507$).
[e] Uncertainty measure based on Baker et al. (2015) (1985:M1–2015:M3, $T = 363$).
[f] Uncertainty measure based on Bachmann et al. (2013) (1973:M1–2011:M12, $T = 468$).

The top panel of Table A-1 provides some summary statistics for the six uncertainty measures used in our analysis. Not too surprising, the coefficients of variation for the uncertainty proxies derived from equity valuations tend to be larger compared with those of uncertainty proxies that are not based on financial market data. As evidenced by the partial correlations, all measures exhibit significant positive first-order autocorrelation; the degree of serial dependence, however, dies off very quickly in every case. Letting each series follow an AR(3) process, there is no evidence of parameter instability in the autoregressive coefficients, according to the Elliott and Müller (2006) Quasi-Local Level test. Moreover, in most cases, the resulting residuals appear to be distributed randomly.

As shown by the entries in the bottom panel, the six series, in general, exhibit significant positive contemporaneous correlation. As expected, the highest degree of comovement is between the three uncertainty proxies based on the stock market data (RVOL, IVOL, and VXO). The other three measures (JLN, BBD, and BES) are also positively correlated with their equity-based counterparts, though to a noticeably lesser extent. The pairwise correlations between JLN, BBD, and BES, in contrast, are appreciably lower.

B Estimation Appendix

As discussed in the main text, we follow Del Negro and Schorfheide (2011) to implement the Minnesota prior on the reduced-form coefficients $\{\mathbf{B}, \boldsymbol{\Omega}\}$ through dummy observations. The Minnesota prior is specified conditional on five hyper-parameters, denoted by $\lambda_1, \ldots, \lambda_5$. The hyper-parameter λ_1 controls the overall tightness of the prior; λ_2 scales the prior standard deviation of the coefficients associated with the lags of the endogenous variables; λ_3 controls the prior on $\boldsymbol{\Omega}$; λ_4 controls the prior for the intercept; and λ_5 controls the prior correlation between the coefficients.

TABLE B-1: Values for the Hyper-Parameters of the Minnesota Prior

Uncertainty Proxy (Sample Period)	λ_1	λ_2	λ_4	λ_5
JLN (1973:M1–2015:M3)	1.07	1.79	2.41	4.29
JLN (1973:M1–2007:M12)	1.17	1.78	2.36	4.16
RVOL (1973:M1–2015:M3)	1.64	1.79	2.46	2.52
IVOL (1973:M1–2015:M3)	1.70	1.67	2.48	2.20
VXO (1986:M1–2015:M3)	1.34	2.39	9.14	2.60
BBD (1985:M1–2015:M3)	1.83	2.43	5.37	2.18
BES (1973:M1–2011:M12)	1.76	1.65	2.54	2.00

NOTE: The entries in the table denote values for the specified hyper-parameter.

We select the hyper-parameters and the VAR lag length p by maximizing the marginal data density. To perform this optimization, we use the version of the CMA-ES evolutionary algorithm proposed by Hansen et al. (2003). The only hyper-parameter we do not select optimally is λ_3, which we set equal to 1. Table B-1 tabulates the model-specific hyper-parameters that maximize the marginal data density. The optimal VAR length for all models is $p = 6$. We use the Direct Monte Carlo Sampling algorithm of Zellner (1971) to obtain draws of the reduced-form parameters from the posterior distribution.